Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in U.S. Hospitals

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We use a social contagion lens to study the dynamic, temporal process of the diffusion of electronic medical records in the population of U.S. hospitals. Social contagion acknowledges the mutual influence among organizations within an institutional field and implicates information transmission through direct contact and observation as the mechanisms underlying influence transfer. We propose hypotheses predicting a hospital's likelihood of adopting electronic medical records as a function of its susceptibility to the influence of prior adopters, the infectiousness or potency of influence exerted by adopting hospitals, and its social and spatial proximity to prior adopters. Results obtained by fitting a heterogeneous diffusion model to data from a sample drawn from an annual survey, spanning 1975 to 2005, of almost 4,000 U.S. hospitals suggest that diffusion can be accelerated if specific attention is given to increasing social contagion effects. In particular, with respect to susceptibility to influence, greater hospital size and age are positively related to the likelihood of adoption for nonadopters, whereas younger hospitals are associated with greater infectiousness for adopters. A hospital's "celebrity" status also contributes to its infectiousness. We further find strong effects for social proximity and significant regional effects for spatial proximity and hospital size, suggesting that geographical covariates should be included in diffusion studies. Results also reinforce the importance of theorizing about and including interactions in examinations of social contagion.

Key words: electronic medical record; diffusion; social contagion; propensity; susceptibility; infectiousness; spatial and social proximity
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1. Introduction

Why do firms in an industry adopt new technologies at different rates? What mechanisms influence the diffusion of technological innovations across a population of potential adopters? These questions have been of importance to researchers and policy makers who are interested in the swift adoption of new technologies and processes that may increase social welfare. The health-care industry is a compelling example of a population that exhibits significant variation in the rate at which hospitals adopt and accept technological innovations. Indeed, it has become popular to suggest that the health-care system in the United States is broken and that information technology (IT) enabled transformations are vital for the industry (Lorenzi

et al. 2005). Yet, hospitals have been strikingly slow to adopt IT (Ash and Bates 2005, Bates 2000, Bower 2005, DesRoches et al. 2008, Jha et al. 2009). Because IT can alleviate persistent problems such as patient safety concerns, medical errors, and escalating costs, accelerating its diffusion is a crucial public policy issue (Bower 2005, Bush 2004, Pan et al. 2004). Health IT (HIT) has assumed center stage in recent discussions of health-care reform, and the U.S. government has increasingly turned to mandates and incentives for speeding up adoption rates.[1]

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[1] On February 17, 2009, U.S. President Barack Obama signed into law HR 1, the American Recovery and Reinvestment Act, which allocates $19.2 billion dollars in funding to support the adoption

Electronic medical records (EMRs) are one of the foundational but nonetheless controversial technologies for digitization of health care. An EMR is a digital repository of patient data that is shareable across stakeholders, such as clinicians, insurance companies, employers, and within a hospital and/or health system. Typical EMR *systems* incorporate features such as a clinical data repository, computerized patient records, decision support applications, integration with other systems, and transaction processing capabilities. The EMR has been characterized as one of the significant innovations to emerge in the health-care industry in recent years (Jha et al. 2009). It offers the promise of unifying fragmented data and applications and allows the practice and administration of medicine to incorporate more evidence-based decision making (Elson and Connelly 1995). Yet, it also raises concerns about physician control, privacy (Gostin and Hodge 2002), and implementation costs (Hartley and Jones 2005). Furthermore, some argue that the benefits of HIT in general and EMRs in particular have yet to be proven and that there are unintended consequences with its use (Ash et al. 2004, Chaudhry et al. 2006, Koppel et al. 2005, Wachter 2006). Therefore, it is not surprising that the diffusion of EMRs across the United States has been slow (Ash and Bates 2005, Bower 2005). Though the technology has been available commercially for over three decades, studies show that its adoption rates are consistently below 30%, with some estimates as low as 7.6% for a basic electronic health record (EHR)[2] system (Jha et al. 2009),[3] underscoring the uncertainty hospitals confront in their decision to acquire the innovation (Greve 2009).

A variety of theoretical perspectives have been used to investigate the adoption and diffusion of innovations. Prior studies have used variance models to study the penetration of IT innovations in a population, where a firm's inherent propensity to adopt the innovations has been predicted according to organizational factors such as size, structure, and resources (Fichman 2004). Such models have implicitly assumed that the adopting entity's decision is primarily a function of its internal resources and traits. However, organizational actions are deeply influenced by those of other referent entities within a given social system (DiMaggio and Powell 1983): nonadopters are influenced by adopters over time, and they influence the actions of other nonadopters after their own adoption of the innovation. In other words, diffusion is a *temporal* process of *social* contagion.

We use a social contagion lens to investigate the processes underlying the diffusion of EMRs across the target adopter population of U.S. hospitals. Contagion occurs through observation, information transmission, and learning. It offers a rich theoretical frame for examining the diffusion dynamics of EMR adoption by hospitals. First, the EMR itself is the "great connector" within the health-care system, and it offers significant network externalities. Though some benefits of ownership will accrue to the owners of stand-alone EMRs (Schmitt and Wofford 2002, Wang et al. 2003), exponential value is expected when EMRs are linked across care providers, allowing the seamless transfer of medical information (Hillestad et al. 2005, Pan et al. 2004). Therefore, some regional players are forming coalitions to connect both affiliated and competitive providers. These coalitions create new mechanisms for disseminating information and shared understanding among entities, and increase the visibility and salience of hospitals' actions to peers within the community.

Second, hospitals compete through management practices and the ownership of medical technologies and specialized skills, rather than administrative technology or treatment innovations (Christensen et al. 2009). In the case of patient management and treatment, it is considered unethical to withhold knowledge about effective (or ineffective) methods from other providers of care. Thus, extensive outlets exist for communicating these innovations to the broader population of providers, including such forums as trade journals, academic publications, conferences, and vast networks of member organizations and special interest groups. Finally, it is notable that the hospitals themselves do not "protect" their innovations via patents or other intellectual property mechanisms, further resulting in greater transparency and information sharing.

Drawing on social contagion, we propose hypotheses about a hospital's likelihood of adopting EMRs as a function of its susceptibility to the influence of prior adopters, its proximity to prior adopters, and the infectiousness or potency of influence exerted by adopting hospitals. Using archival data from a sample drawn from an annual survey spanning 1975 to 2005 of almost 4,000 U.S. hospitals, we apply a heterogeneous diffusion model (HBM) technique to perform a temporal analysis of the dynamic contagion

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and use of health information technology (see Title XIII entitled the "Health Information Technology for Economic and Clinical Health Act" or the "HITECH Act").

[2] The terms EHR and EMR have been used synonymously in the literature; however, in 2008 the National Alliance for Health Information Technology suggested that the term EMR be used for electronic record systems that are not interoperable, and that EHR be used when health information is shared electronically among multiple entities. In this paper, the terms EHR and EMR should be assumed to be synonymous.

[3] All studies of EHR adoption prior to Jha et al. (2009) yielded significantly higher rates of adoption, typically ranging from 10%–30%. The lower rate reported in the Jha et al. (2009) study is due to a more stringent definition of EHR.

process. We find the infectiousness of hospitals that have adopted, as well as a focal hospital's susceptibility to influence, are heterogeneously distributed in the population. We also find strong effects for social proximity on a hospital's likelihood of adoption, and regional effects for spatial proximity.

Our work departs from prior examinations of the IT diffusion process in several key respects. First, although others have applied concepts of social contagion to understand the adoption (and abandonment) of organizational practices across populations of firms (e.g., Gaba and Meyer 2008, Greve 1995), ours is one of the first studies to rigorously examine the dynamics of the contagion process in the context of complex IT adoptions. Second, though prior research has examined the adoption of EMRs, a majority of the studies provide cross-sectional snapshots of the phenomenon, limiting their ability to understand how the actions of other hospitals within the national ecosystem of health-care providers influence potential adopters. Finally, from a methodological perspective, this represents one of a handful of studies to apply the HDM technique to study social contagion. HDMs offer robust estimation methods to empirically demonstrate the dual roles that entities can play both as targets and sources of influence.

The remainder of this paper is structured as follows. In the next section, we present the theoretical background and develop the research hypotheses. This is followed by a description of the methods employed, including the data, variable operationalization, and analysis techniques. Finally, we present results and end with a discussion of limitations, and theoretical and practical implications of the findings.

2. Theoretical Background

The adoption and diffusion of innovations has been examined in multiple disciplines and from a variety of theoretical perspectives (for review, see Wejnert 2002, Strang and Soule 1998, Fichman 2004). Given our theoretical stance of innovation diffusion as a process of social contagion, we provide a brief review of the relevant literature, followed by a discussion of the nature of IT-based innovations in general and EMR systems in particular.

Table 1 summarizes research that has examined the drivers and facilitators of EMR adoption. Three observations are noteworthy. First, aside from Miller and Tucker (2009), most studies have used cross-sectional data and ignored the temporal nature of EMR adoption and contagion effects caused by other hospitals' adoption. They have used standard regression techniques in their empirical analyses. Second, no study has adopted the social contagion lens, limiting insights about the mutual and contingent influence between organizations in the same institutional field. Prior research does not elaborate the "logics that turn diffusion channels off and on," (Still and Strang 2009, p. 60). Finally, none of these studies incorporated changes that are taking place in these covariates over time and the effect of these changes on adoption.

2.1. The Process of Social Contagion

The term "contagion" originated in biological sciences and is popularly used to signify the spread of disease through touch or other forms of close contact among individuals. le Bon (1895) offered one of the earliest treatments of *social* contagion and is famously credited with describing "the crowd," where the collective rather than individual mind takes precedence as a determinant of behavior. Studies of social contagion have been conducted in multiple contexts including the spread of hijacking attempts (Holden 1986), diffusion of consumer durables (Van den Bulte and Stremersch 2004), and the adoption of civil service reforms (Tolbert and Zucker 1983). Although contagion is frequently understood to connote the diffusion of an idea or practice through a social system, there is little agreement about its precise definition, or the diffusion mechanisms underlying it (Gaba and Meyer 2008). For instance, Marsden (1998) points to multiple interpretations of the term in extant literature, including aspects of "noncriticality" (i.e., those affected do not evaluate the idea being transmitted rationally and systematically) and nonintentionality, in that the recipient does not perceive the influencer to be exerting influence intentionally. Still and Strang (2009, p. 58) likewise note, "diffusion research develops little insight into the motives and mechanisms that underlie interorganizational influence." Nonetheless, whether social pressure is overtly analyzed a priori or it simply induces an automatic nonreflective response, there is broad agreement that contagion results in an increasing prevalence of the focal innovation in the population under study (Strang and Soule 1998).

What are the fundamental mechanisms underlying social contagion in the ecology of organizations? Contagion occurs either through the direct transmission of information during interactions between adopters and nonadopters, or via an observational process where managers scrutinize their environment and attend to the adoption decisions of other organizations (Strang and Soule 1998). Theoretically, the literature views all prior adopters as "carriers" or sources of contagious influence (Greve 1995). Thus, the sheer number of adoptions by actors within a given population[4] drives subsequent adoption (e.g.,

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[4] The phenomenon of prior adoptions encouraging subsequent adoption is one result of the presence of network externalities, where "an increase in the number of users of a good increases the value to other users" (Gowrisankaran and Stavins 2004, p. 260).

Table 1   Prior Work Investigating Determinants of EMR Adoption in the U.S. Health System

Authors	Theoretical logic	Data and method	Dependent variable	Predictors
Kazley and Ozcan (2007)	Resource dependency theory: organizational and environmental factors drive EMR adoption	• National cross-sectional data on hospital EMR adoption in 2004; 4,606 cases • Logistic regression	*EMR adoption* in 2004	• Environmental factors (competition, urban[+], per capita income, change in unemployment rate[+]) • Organizational factors (size[+], ownership, system affiliation[+], public payer mix, teaching status, financial resources)
Simon et al. (2007)	Organizational and market related factors that influence EMR adoption should affect the adoption of computerized physician order entry (CPOE) with computerized decision support system (CDSS)	• Cross-sectional survey of 1,104 physician organizations (medical groups and independent practices) • Logistic regression	*CPOE with integrated CDSS adoption*	• Organizational characteristics (size, age, number of clinic locations, ownership) • Market characteristics (managed care penetration in local market, rurality, external incentives for improving quality[+])
Miller and Tucker (2009)	Network benefits related to ability to exchange information with other hospitals (interoperability) drive EMR adoption: installed base of EMRs in region interacts with state level hospital privacy laws	• Both time-series and national cross-sectional data • Hospital EMR adoption in 2005; 3,988 cases • Panel data on state-level hospital privacy laws • Linear probit	*EMR adoption in* 2005	• Network effects[+] (installed base of EMRs in local health service area (HSA)) • Network effects × state-level hospital privacy laws (in states w/o privacy laws[−], in states w/ privacy laws not signif.) • Controls (size[+], age, academic[+], number of hospitals in HSA[−])
Markle Foundation (2004)	Incentives should increase the uptake of EMRs	• Cross-sectional survey	*Incentive required for adoption*	• Direct incentives for HIT adoption estimated at $24,000 per physician[(na)]
Harrison et al. (2007)	Conceptual paper positions HIT adoption in a framework described by Interactive Sociotechnical Analysis (ISTA)	• Literature review and conceptual development	Not applicable	• The fit between new HIT and existing technical and physical infrastructures is important[(na)]
Jha et al. (2006)	Surveys investigating EHR adoption need to explicitly define the technology. Adoption of EHRs varies by practice size and type	• Literature review of extant survey research conducted between 1995 and 2005, investigating HIT adoption	*Adoption rate of EHRs among health providers*	• Limited hospital data available but found adoption rates in practices varied considerably, with larger practices having greater rate of adoption[+]
Bates et al. (2003)	Literature review and conceptual paper discussing benefits and barriers related to the adoption of electronic medical records	• Literature review and conceptual development	Not applicable	• Discusses the barriers to adoption of EMRs at the practice level. Two key barriers identified are relevant in the hospital context: privacy and security of data and physician resistance[(na)]

Table 1   (Continued)

Authors	Theoretical logic	Data and method	Dependent variable	Predictors
Jha et al. (2009)	Exploratory investigation based on prior work using organizational and market related factors to determine EHR adoption	• National cross-sectional data on hospital EHR adoption as of 2008 for 2952 acute care hospitals • Defined two levels of adoption: basic and comprehensive EHR functionality	*Adoption of EHR* (expert-consensus defined)	• Hospital characteristics and factors that have been cited as barriers and facilitators such as size[+], academic[+], urban[+], for profit[−], system member[+], capital requirements[−], and maintenance costs[−]

Notes. Statistical significance is identified by $+$, $-$, or (na) (not applicable). If predictor is not statistically significant, no sign is noted.

Gaba and Meyer 2008). However, the dynamics of the influence process are far more complex. A focus on simple prevalence alone makes the erroneous assumption that all nonadopting entities within a system are equally likely to be affected, and that all prior adopters exert homogeneous influence (Strang and Tuma 1993). Such assumptions of spatial and temporal homogeneity ignore the social structure of the population under study in three respects (Strang and Tuma 1993).

First, the effects of influence are likely to be heterogeneously experienced by nonadopters because of variations in their immunity to influence. Wejnert (2002, p. 320) alludes to this heterogeneity: "the actor's characteristics will modulate both the process of information intake and the process of whether to adopt an innovation." Second, it is well known that physical or social proximity plays a role in the transmission of information and influence (e.g., Gaba and Meyer 2008). Therefore, the degree to which the influencee is proximate to the contagion source affects the potency of the influence. This notion is implicit in studies adopting a social network perspective, where, for example, it is argued that structural relationships such as linkages or ties between organizations affect the rate and extent of influence transmittal (Ahuja 2000), or that corporate contacts' behavior is more influential than the behavior of an organization outside a specific reference group (Greve 1995, Rao et al. 2000). Finally, the characteristics of the influence carrier determine infectiousness. Entities within any social system are differentiated. Some are influential because they are exemplars that others seek to emulate (Ashforth and Humphrey 1997), and their behaviors garner more managerial attention (Rindova et al. 2006). Therefore, the adoption decision of some organizations is more consequential for nonadopters.

2.2.   The Nature of IT Innovation and EMRs
Innovation typologies describe the characteristics of innovations (Damanpour 1991) and include categories such as administrative and technical (e.g.,

Daft 1978, Damanpour 1987), radical and incremental (e.g., Dewar and Dutton 1986, Nord and Tucker 1987), or product and process innovations (e.g., Daft 1978). However, all innovations are innately fraught with uncertainty, and managers face considerable risk in the adoption decision. For IT innovations in particular, scholars have observed that they are often complex and that organizations face significant "knowledge barriers" in successfully deploying them (Attewell 1992, Fichman and Kemerer 1997, Paré and Trudel 2007). Though an organization might make an initial investment to adopt a new technology, there is robust evidence of an "assimilation gap" when the organization is unable to successfully implement and deploy the acquired technology (Fichman and Kemerer 1997).

Enterprise-wide technologies are complex, and their implementation causes substantive changes in processes, work routines, and established patterns of interaction among organizational actors (Brynjolfsson and Hitt 2000). Studies of the implementation of enterprise resource planning systems point to high failure rates caused, in part, by the inherent complexity of the technology (Weston 2001). Swanson (1994) characterizes such technologies as "Type III" innovations that integrate IT products and services with other business technologies, and have a wide ranging operational and strategic impact on the business. Though such Type III innovations may offer considerable benefits, the ambiguity surrounding an organization's ability to appropriate the value implies that the decision to adopt is fraught with managerial risk and uncertainty.

Descriptions of the functionality of EMRs (Acs et al. 1994, Ash and Bates 2005) and studies of EMRs in practice (Greatbatch et al. 1995, Warshawsky et al. 1994) suggest that they are complex innovations that cause major shifts in the work practices of clinicians and other personnel (e.g., Makoul et al. 2001). EMR systems involve multiple users, with varying levels of skill and experience. Some are well-trained administrators, but others use the system occasionally or

superficially (Lapointe and Rivard 2005, Sánchez et al. 2005). Sánchez et al. (2005) note that EMR implementations must be successful on several dimensions: effectiveness, efficiency, organizational attitudes, user satisfaction, and patient satisfaction. Thus, the scale and scope of the organizational change precipitated by EMR systems is substantial, and it is evident that hospitals would face considerable knowledge barriers to implement them successfully. The fact that the vast majority of hospitals have yet to adopt EMRs reinforces the uncertainty surrounding the benefits of adoption. Documented high-profile hospital IT project failures, which have resulted in investment losses in the tens of millions of dollars (Ornstein 2003, Scott et al. 2005), as well as studies that have reported negative results of EMR adoption (Harrison et al. 2007, Koppel et al. 2005) intensify the risks that managers assume in their EMR adoption decisions. Social contagion theory suggests that when performance is uncertain, decision makers will seek insight from others within their ecosystem (DiMaggio and Powell 1983, Mansfield 1961).

Thus, theories of social contagion implicate information transmission via direct contact or observational processes as microprocesses underlying the spread of an innovation through a population (Strang and Soule 1998). We have argued that, like many technology-based innovations, EMRs pose considerable knowledge barriers for organizations. In turn, this creates much uncertainty in the minds of potential adopters about whether and when to adopt. The actions of prior adopters can serve as a powerful source of uncertainty reduction about the risks and benefits of the innovation. The degree to which contagion occurs is a function of the source of influence, the recipient of the influence, and the relationship between the source and recipient. How is social contagion between hospitals manifested in the context of the complex technological innovation encapsulated in the EMR? We propose specific hypotheses to elaborate upon this process.

3. Hypotheses

3.1. Susceptibility to Contagious Influence
Within any institutional field, organizations are influenced by each other in a variety of ways. Gaba and Meyer (2008) examined within-population contagion in the context of the adoption of corporate venture capital programs by IT firms and argued that the extent of adoption among peer firms represents a potent source of social influence for nonadopters. They note that this expectation is supported by multiple theoretical rationales, including neoinstitutional theory that posits the existence of a process of mimicry (DiMaggio and Powell 1983), vicarious

or social learning where the actions of others serve as a basis for one's own behavior (Bandura 1977, Haunschild and Miner 1997), or simply rational-choice arguments that greater adoption within the population signals beneficial outcomes (Rogers 1995).

Though all nonadopters experience such influence to some degree (a *baseline* contagion effect), the contagion lens proposes that there is variation in organizational susceptibility to this influence (Strang and Tuma 1993). Individual organizations draw upon their experience and resources in forming their interpretations about an ambiguous environment (Milliken 1990). The effects of prior adoption of EMRs on current nonadopter hospitals are modulated by their experience and knowledge (BarNir et al. 2003). In particular, we expect that hospital age and size will amplify the effects of prior adoptions. Established firms understand the importance of external information, particularly when confronting an uncertain environment (Meyer 1982). Older and larger firms recognize the significance of institutional legitimacy within an organizational field, and managers within such firms tend to conform to the dominant strategic actions of others in their industry (Still and Strang 2009).

In health care, it is a truism that the environmental pressure for systemic change has existed for over five decades. However, it has not altered the institutional structure significantly because of political and social resistance. Older hospitals have more experience and are able to recognize that increasing adoption of an innovation among their peers signals the emergence of a new basis for competitive parity. Therefore, they are likely to be more susceptible to the influence of prior adopters. Experience can be accumulated through environmental scanning (Thomas et al. 1993) or through the knowledge embedded within individuals and organizational routines (Daft and Weick 1984). Once gathered, the information is interpreted using an organizational framework, and an action is planned (Gioia 1986). Although the interpretation is often considered to be a managerial process, organizations are interpretation systems because scanning and sensemaking take place in a multitude of ways by a variety of people (Daft and Weick 1984). Larger organizations have more personnel resources and have more opportunities for environmental scanning. Therefore, larger hospitals are more likely to notice the new adoption.

Furthermore, larger and older organizations are likely to have more direct ties to external entities because they have more employees and greater legitimacy earned through longevity. They can amplify their opportunities for social learning through direct transmission of information about the innovation. For

example, larger hospitals have more consulting physicians who work at other hospitals (Pisano et al. 2001). This heightens the possibility of a direct contact in a hospital that is a current adopter of EMRs. Finally, even if smaller hospitals have appropriate scanning processes in place and are able to observe the actions of peers with some degree of certitude, they face significant knowledge and resource barriers with respect to the successful assimilation of a complex technological innovation. Knowledge barriers can elicit a rational response from the hospital to choose not to attend to the adoption of EMRs by other hospitals, simply because it has low efficacy with respect to its own ability to innovate. Wejnert (2002) suggests that the economic conditions of the actor determine their susceptibility to influence, and a lower resource endowment in a smaller hospital may likewise elicit a response to ignore the actions of others. In other words, social influence from adopter hospitals may provide smaller hospitals with the motivation to change, but this is tempered by limitations in their ability to innovate, thereby inhibiting action (Greve 2005). The opposite is true as well: to the extent that larger hospitals have more slack resources,[5] this will enable them to act on new information when it becomes available (Nohria and Gulati 1996). This logic leads us to predict the following:

HYPOTHESIS 1A (H1A). *Older nonadopter hospitals are more susceptible to the contagious influence of prior adopters than are younger nonadopter hospitals.*

HYPOTHESIS 1B (H1B). *Larger nonadopter hospitals are more susceptible to the contagious influence of prior adopters than are smaller nonadopter hospitals.*

An institution's decision to adopt unfolds in a complex environmental and social milieu where a multitude of influence sources coexist. Therefore, certain factors would have amplifying or attenuating effects on contagion outcomes. In reviewing the literature on diffusion of innovations, Wejnert (2002) observes that the investigation of interactions among diffusion covariates needs further study. Size and age are two important and recurrent predictors of organizational response to innovation (e.g., Damanpour 1991). Although these organizational characteristics have been included in several diffusion studies, Greve (2005) notes that the interaction of size and age has received less attention in the literature. We theorize that age will substitute for size with respect to susceptibility to contagion. Conceptually, a *substitute*[6] is said

to replace or act in the place of another (Kerr 1977). In prior studies, substitution effects have been shown to exist when main effect variables act through similar conceptual means to affect the outcome variable (Howell et al. 1986) and when there is a correlation between the two predictor variables (Podsakoff et al. 1996). For example, Podsakoff et al. (1993) show that group cohesiveness, indifference to organizational reward, and intrinsically satisfying tasks are good substitutes for leadership skill as it relates to performance, role perceptions, and subordinate attitudes.

We suggest that larger hospitals have more channels for internalization of external information and a greater endowment of knowledge resources. Some of the benefits of size are similar to those garnered from maturity and enable hospitals to be more diligent in environmental scanning. Mature (i.e., older) hospitals have more established relationships to support greater environmental scanning. Therefore, there is likely to be an overlap in the resources used to acquire environmental knowledge. This logic suggests that hospital age substitutes for size as a driver of susceptibility to contagion. Therefore, we hypothesize the following:

HYPOTHESIS 1C (H1C). *Age is a substitute for size in its positive relationship with susceptibility to the contagious influence of prior adopters.*

3.2. Infectiousness of Carriers

In the absence of direct experience, managers facing uncertainty about the decision to adopt a risky and complex technological innovation frequently turn to the actions of others. This idea is central to the social learning process of behavior modeling where the "role model" is frequently an admired and respected actor (Bandura 1977). Institutional isomorphism argues that managers often look to admired firms for direction, especially while assessing the desirability of adopting complex innovations or practices (DiMaggio and Powell 1983). Thus, the actions of reputed firms are likely to be especially infectious in spurring other firms toward adoption of innovations. Nonadopter firms may respond in mimetic ways to highly infectious carriers or adopter firms (March and Olsen 1976). A firm's status or reputation may be an outcome of many factors including financial performance, strategic posture, advertising expenditures, or perceived social responsiveness (Fombrun and Shanley 1990).

What types of hospitals are more likely to be emulated by others? We draw upon the literature on "celebrity" firms (Rindova et al. 2006), whose actions are likely to be highly influential to nonadopters. Celebrity firms are "those firms that attract

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[5] Nohria and Gulati (1996) argue for a curvilinear relationship between slack and innovation such that too little or too much slack results in diminishing innovation. Other than these extremes, the relationship is positive and linear.

[6] We discuss the empirical handling of substitutes in §5.3 and Footnote 10.

a high level of public attention and generate positive emotional responses from stakeholder audiences" (Rindova et al. 2006, p. 4). The media identifies such leaders or celebrity firms in the journal *Hospitals & Health Networks*, which releases an annual list of the nation's "100 Most Wired Hospitals and Health Systems." It is a compilation of highly acclaimed (celebrity) hospitals. Studies have found that hospitals on the Most Wired list are truly high-performing firms and have better overall care in the areas of mortality rates, patient safety, and average length of stay (Bates 2002). A qualitative assessment also suggests that patient flow and workflow are better in Most Wired hospitals (Solovy 2007). Thus, in addition to representing leading edge practice in the use of IT, these hospitals have overall superior performance. As a current nonadopter hospital scans its environment and seeks to establish legitimacy by emulating prestigious role models, we expect that EMR adoption by celebrity hospitals will exert a relatively more potent social influence.

Hypothesis 2A (H2A). *Within the population of adopters, the infectiousness of celebrity adopter hospitals is stronger than the infectiousness of noncelebrity adopter hospitals.*

The visible accolades and recognition that celebrity hospitals garner underscore their importance as role models. In addition to this overt acknowledgement of an organization's celebrity status as a signal for emulating behavior, decision makers frequently seek other indicators of "whom to imitate." In their study of the diffusion of hate crime legislation in U.S. states, Soule and Earl (2001) found states to be more influential when there was disparity in political leanings between the governor and the majority legislature, primarily because these differences encouraged press coverage. Others have used characteristics of the focal entities (i.e., network centrality) (Strang and Tuma 1993) and characteristics of the event itself (i.e., the severity of a riot) to explicate infectiousness (Myers 2000).

We argued earlier that larger and older nonadopter firms are more susceptible to contagion. In a contagion context, it has been noted that the effects of some covariates are highly nuanced in that they can simultaneously act to dampen susceptibility and increase infectiousness or vice versa (Greve et al. 1995). We now examine organization size and age once again and suggest that size has a positive influence on infectiousness and age exhibits a negative association.

Infectiousness is a social phenomenon, and the act of noticing not only falls upon the seekers of information but also upon those who desire to be noticed. Larger hospitals have greater access to more resources to publicize various achievements, such as the adoption of a complex information technology. Through

such dissemination of accomplishments, organizational legitimacy can be achieved if the actions are perceived as "desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions," (Suchman 1995, p. 574). Though findings about the role of size in cognitive legitimacy have been mixed (Deephouse 1996), most studies have noted that legitimacy benefits result from increased organizational size (Dobbin et al. 1988). To the degree that such legitimacy makes larger hospitals more attractive role models, we predict the following:

Hypothesis 2B (H2B). *Larger adopter hospitals are more infectious than smaller adopter hospitals.*

Organizational age is frequently associated with openness to new ideas, ability to successfully innovate, and a general receptivity to change (Damanpour 1991). Younger organizations are the harbingers of technologies and products that are likely to change the industry, and entrant firms are typically associated with the highest probability of innovation (Huergo and Jaumandreu 2004). In a setting characterized by frequent technological change, it is plausible that hospitals will scan the environment for pioneers of new ideas so that they can gain insight into the shape of things to come. Information-based theories argue that imitation occurs because the to-be-followed firm is perceived as having superior foresight about potential transformations. Lieberman and Asaba (2006) discuss the business-to-business start-up boom of the late 1990s that led to herd behavior in which scores of large businesses attempted to follow the actions of an unproven business model constructed by small new entrants because they viewed them as having superior insights or ideas about a new organizational form. Younger organizations are less likely to be fettered by legacy and are more willing to adopt and experiment with technological innovations. Within their industry or community, more established or older firms could learn vicariously through observations of their younger counterparts' experiments and actions. This leads us to predict the following:

Hypothesis 2C (H2C). *Younger adopter hospitals are more infectious than older adopter hospitals.*

An implicit assumption in the conceptualization of infectiousness as a property of the influencer is that nonadopters attend to and notice the infected carrier. As in the case of susceptibility to influence for nonadopters, we theorized that the size and age of prior adopters act independently to increase their strength of influence. Youth signals openness to new ideas, whereas size signals legitimacy. However, *collectively*, these two traits can create a different perception for nonadopters. When size and age are at opposite extremes, this may suggest either an implied lack

of maturity or an absence of strategic focus, both of which are likely to make a hospital less desirable as worthy of emulation. From a legitimacy standpoint, for two hospitals of similar size, there is a liability associated with being young such that the combination yields a potentially high-risk role model. Furthermore, an older and smaller hospital may signify reluctance to change and is unlikely to garner attention from others. Thus, we expect the following:

HYPOTHESIS 2D (H2D). *The relationship between hospital size and infectiousness is significantly influenced by hospital age.*

3.3. Physical and Social Proximity to the Contagion Source

A core tenet underlying the social contagion logic of diffusion is that actors within a "network" influence each other through interaction and observation (Gaba and Meyer 2008). A network of organizations may be defined using a physical metaphor in the form of *spatial proximity*. Alternatively, it may be viewed through a more traditional lens of interpersonal contacts between individuals. In the former case, Strang and Soule (1998, p. 275) assert that "No distinctive logic can be proposed—rather, spatial proximity facilitates all kinds of interaction and influence." Physical proximity creates more opportunities for managers to observe and notice the actions of others related to innovation adoption, and also increases the likelihood of knowledge spillover. Such localized knowledge spillover (LKS) has been defined as " 'knowledge externalities bounded in space,' which allow companies operating nearby the knowledge sources to introduce innovations at a faster rate than rival firms located elsewhere" (Breschi and Lissoni 2001, p. 975). The LKS literature notes that the adoption of highly complex information systems requires specific and tacit knowledge (Zander and Kogut 1995). Because this knowledge is not codified, the ability of firms to process detailed information is limited (Simon 1991, Wang and Chen 2004). Therefore, geographic proximity to other adopters is very important (Breschi and Lissoni 2001, Doring and Schnellenbach 2006, Zander and Kogut 1995). The required tacit knowledge can be spread through face-to-face interaction, personal relationships, or simply because there is knowledge transfer when workers leave one firm for another. All of these factors tend to occur with greater frequency when the distance between entities decreases (Breschi and Lissoni 2001). In essence, LKS aids hospitals in overcoming the knowledge barriers inherent in a complex innovation such as EMRs.

LKS is likely to be especially prevalent in hospitals because of the nature and organization of medical work. Physicians are typically "free agents" who maintain their own practice but have referral and admitting privileges to hospitals within a circumscribed geographic area. A physician using EMR technology in one hospital becomes a natural source of experiential knowledge when she interacts with colleagues in a nonadopter setting. This type of "informational" social influence (Deutsch and Gerard 1955) is critical for disambiguating the innovation for the potential adopter. Thus, we predict the following:

HYPOTHESIS 3A (H3A). *Spatial proximity to prior adopters is positively associated with the nonadopter's likelihood of adoption.*

Social proximity or membership in a social group is also important for contagious influence. Behavior is influenced by informational exchanges during formal and informal interactions (e.g., Cacioppo et al. 1982). Social proximity engenders trust (Castaldo 2008, Putnam 1995), and influence is more readily transmitted among trusted parties. For hospitals, we posit that social proximity can be represented as membership in a health system; i.e., hospitals belonging to the same health system are part of the same social network. A majority of U.S. hospitals (approximately 67%) are part of a health system (Federal Trade Commission and Department of Justice 2004). Health systems include affiliated hospitals, physician practices, clinics, and heath centers. We expect that the adoption actions of other hospitals within the focal hospital's health system will be more influential than others outside of the health system. Though there is no universally accepted model for managing a health system (i.e., centralized versus de-centralized versus federated decision making), even in a decentralized model, there will be strong influence from other hospitals within the health system to conform to a set of standard operating procedures. In a centralized model, with technology decisions being made at the corporate level, there is an even greater likelihood that EMR adoption will be a function of the influence from hospitals within the health systems. Managers in nonadopting hospitals will benefit and learn from the tacit knowledge related to technology implementation that others within their social system have acquired. They may believe that the experience of their close contacts will mitigate technology adoption risks through the sharing of best practices and lessons learned. Prior research has found that when network actors are in close social proximity, the density of actors who have already adopted is an important influence on intranetwork adoption rates (Blau et al. 1992, Knoke 1982). To the extent that adoption within the network signals

a lower risk of adoption and helps resolve uncertainty, we predict the following:

HYPOTHESIS 3B (H3B). *Adoption by a hospital within the focal hospital's health system (in-system) is more positively associated with likelihood of adoption than adoption by a hospital outside the focal hospital's health system (out-system).*

4. Methods

4.1. Data

The data for hypothesis testing comes from a nationwide, annual survey of care delivery organizations in the United States, conducted by HIMSS Analytics™. The HIMSS Analytics Database (derived from the Dorenfest IHDS + Database™) used in this study spans 1975–2005 and provides information about 3,989 hospitals, excluding government-owned facilities, collectively representing approximately 85% of the total number of hospitals in the United States. The database is built by the provider annually through surveys that query chief information officers and other IT executives of hospitals.

4.2. Statistical Model

We apply the heterogeneous diffusion model technique to test the research hypotheses. The HDM is an entity-level model for event history data, and it estimates the hazard rate—the probability of the event occurring in the next time period for a particular actor where the event has not yet occurred—as a function of multiple predictors, while allowing heterogeneity within the population and over time (Strang and Tuma 1993). Because of the interdependent nature of the firms within a social structure (i.e., one firm's actions affect others), other methods cannot overcome the significant challenges of appropriately specifying and empirically validating these relationships (Greve et al. 1995). HDM supports the inclusion of interdependent relationships (contagion) and noncontagion determinants simultaneously within the same model to predict adoption (Greve 1995). Furthermore, it is a stochastic rather than deterministic estimation procedure in that it assumes there is a random distribution in the timing of the events, coupled with random variation within covariates. Contagion mechanisms are fully explicated in HDM such that detailed interrelations can be isolated from the standpoint of the susceptibility of a nonadopter to influence, heterogeneity in influence imparted by adopters (infectiousness), and social proximity within a system (see §EC.1.1 of the e-companion[7] for more details) (Myers 2000, Strang and Tuma 1993, Tuma and Hannan 1984).

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[7] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

We use the multiplicative heterogeneous diffusion model of Strang and Tuma (1993) as implemented in the mhdiff SAS Proc IML macro computer routine (Strang 1995). The population multiplicative HDM estimates a model of the form

$$h_n(t) = \exp\left[\boldsymbol{\alpha}\mathbf{X}_n + \sum_{s \in S_{n(t)}} (\boldsymbol{\beta}\mathbf{V}_n + \boldsymbol{\gamma}\mathbf{W}_s + \boldsymbol{\delta}\mathbf{Z}_{ns})\right], \quad (1)$$

where $h_n(t)$ is the hazard of the event of interest for case n at time t; $\mathbf{X}_n$ is a covariate vector describing the intrinsic propensity of n to experience the event (i.e., adopt); $\boldsymbol{\alpha}$ is the corresponding vector of parameters, net of contagion influences; $S_{n(t)}$ is the set of prior adopters that influence n; $\mathbf{V}_n$ is a covariate vector describing the susceptibility of n to contagious influence from S_t with $\boldsymbol{\beta}$ representing the corresponding vector of parameters; $\mathbf{W}_s$ is a covariate vector of variables that reflect the infectiousness of s in influencing all n; and $\boldsymbol{\gamma}$ is the corresponding vector of parameters. Finally, $\mathbf{Z}_{ns}$ is a covariate vector of proximity variables for n and s (i.e., the pairwise-specific influence of s on n), with $\boldsymbol{\delta}$ representing the corresponding vector of parameters (Strang 1995, pp. 1–2; Strang and Tuma 1993). The population model of Equation (1) is estimated based on sample data using maximum likelihood methods. As explained later, we operationalize the variables in Equation 1 following our theoretical arguments.

4.3. Censored Data

In this study (by most accounts) we have a priori knowledge that more than two-thirds of the hospitals in the United States have not experienced the adoption of an EMR. These nonadopters are an important subset of the data in that these cases are "right censored." Right-censored data implies (1) the hospital will never experience the event, or (2) the hospital will experience the event but not during the time period in which the data are collected (Singer and Willett 2003). Event-history methods incorporate the information that an observation is censored and weight the influence of the case accordingly (Debruyne and Reibstein 2005, Strang and Tuma 1993). We model entry—or in this case, adoption—as a dichotomous event. One advantage of the data used in this analysis is that there is no left censoring, i.e., the first instance of adoption is captured.

4.4. Operationalization of Variables

4.4.1. EMR Event Occurrence. The dependent variable, *likelihood of EMR adoption* (*ADOPT*), is measured using a dichotomous variable (i.e., adopted/notadopted). Drawing from recent definitions, we treat an EMR as an application environment that is composed of the clinical data repository

(CDR), clinical decision support system (CDSS), and the computerized patient record (CPR) (Bower 2005). The EMR event occurrence is operationalized as the adoption of all three components (CDR, CDSS, and CPR). It is not required that all three technologies be adopted in the same year, only that all three are present simultaneously. For example, if a CDR was contracted in 1999, CDSS in 1987, and CPR in 1987, then the EMR event occurrence year is 1999 (see §EC.1.2 of the e-companion).[8] We assume that once the EMR is adopted, it remains in place throughout the timeframe sampled.

4.4.2. Social Contagion Variables. Susceptibility to adoption is a property of nonadopter hospitals and indicates how vulnerable they might be to the adoption actions of other firms (i.e., current adopters). As explained earlier, we expect that size and age and their interaction are variables that predispose a hospital to be more susceptible. Size (*SIZE*) is operationalized as the number of staffed beds, and age (*AGE*) as the number of years the hospital has been in existence.

The infectiousness vector yields an estimate of the differential influence that adopters have on the nonadopter hospitals within the population. Prior research has operationalized infectiousness by identifying characteristics that are thought to be highly sought after and/or influential and appropriately coding the cases that match these characteristics. As noted, we use the journal *Hospitals & Health Networks*'s annual list of the nation's "100 Most Wired Hospitals and Health Systems" as a proxy for celebrity status. We draw data from the annual survey in the years 1999 through 2005 and count the number of times each hospital made the list. Thus, *WIRED* is a scale variable measuring the intensity of the hospital's celebrity, with higher values indicating greater prominence.[9] As might be expected, all *WIRED* hospitals in the population are adopters. Finally, we include *SIZE* and *AGE* of the adopter hospitals and their interaction (*SIZE × AGE*) in parallel as infectiousness covariates. As Greve et al. (1995, p. 416) demonstrate, "multiple

effects of a single variable (and by implication, high correlations among conceptually distinct measures) do not impede estimation when the effects are located in different parts of the model."

Theoretically, we argued for contagion effects arising from two forms of proximity: one based on spatial closeness and a second on social intimacy. For physical proximity, we used an Excel® add-in program (Spheresoft Zip Code Tools) to calculate the Euclidian distance between two hospitals' zip codes. These distances were compiled into a 3,989 by 3,989 matrix of pairwise distances.

Hospitals within the same health system are treated as socially proximate. To model social proximity, we used a "Linked-List" design as described in the mhdiff documentation (Greve et al. 1995), which allows the data to be structured such that links from the focal entity to other entities are specified. This precludes the need for a complex matrix and supports the easy identification of influence channels. In our particular case, for each hospital, we listed the other hospitals (identified by a unique numerical ID) that were part of the focal hospital's health system, and mhdiff, through a matching process, identified which hospitals within the system were adopters and which were not.

4.4.3. Propensity (Control Variables). To eliminate variance for influences that are not a result of social contagion, we include a robust set of controls for firm-specific factors that may have a significant effect on a hospital's adoption decision, i.e., its intrinsic propensity to adopt innovations, independent of contagion effects. Prior research has suggested that this propensity may be a result of the structural aspects of the organization, variations in available resources, and the patient population that the hospital serves. To capture a hospital's propensity to adopt EMRs, we include not only the structural characteristics suggested in prior work (Debruyne and Reibstein 2005, DiMaggio and Powell 1983, Haveman 1993) such as the hospital's size (*SIZE*) and age (*AGE*), but also its stock of IT-related resources, environmental conditions, and geographic region. We include a geographic variable because regional variations in quality of care, Medicare spending, and accessibility to care are well documented (Fisher et al. 2003a, b; Pilote et al. 1995). These propensity-specific variables are *HIT concentration* (*HITC*), *for-profit status* (*PROFIT*), *hospital type* (*TEACH*), *number of state-level HIT initiatives* (*HITINIT*), *percentage of budget devoted to information systems* (*IS BUDGET*), and three regional dummy codes (Northeast (*NE*), Midwest (*MW*), and *South* regions) identifying the Census Bureau region of the country in which the hospital falls. Note that we include the *West* region as the baseline comparator, and thus its results are not presented.

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[8] We note that our study investigates "adoption" rather than "assimilation" or the extent to which an organization has progressed through the assimilation lifecycle for a particular innovation stretching from initial awareness to full institutionalization (Fichman 2001, 2004). Recent data from the HIMSS Analytics EMR Adoption stage model (see HIMSS Analytics 2010) suggests that approximately 80% of hospitals are still in the adoption phases rather than the complex "use" stages.

[9] The *WIRED* variable is not time variant in that it takes on the value of the sum count between years 1999 through 2005 and remains the same in every year. It should be noted, however, that it—like all variables in HDM—is treated differently depending on when the event (EMR adoption) occurs. Because all *WIRED* hospitals are adopters, the variable becomes "active" as an infectious predictor in the year in which adoption occurred and retains that value in every subsequent year.

HITC is defined as the extent to which technologies related to, and/or necessary for, the adoption and use of EMR technologies are already present in the focal firm. The importance of complementary technologies to the success of EMR implementation is significant. Research suggests that the successful implementation of a new technology requires an already existing robust IT infrastructure (Broadbent et al. 1999, Sambamurthy et al. 2003). Because EMRs are often used as the conduit to link and aggregate data across isolated legacy systems within hospitals, it is imperative that other HITs be present for EMRs to perform to their potential. Furthermore, Greve (2005) argues that an organization's capacity to absorb specific knowledge related to an innovation is an important predictor of adoption. We use *HITC* to control for such effects. *HITC* is operationalized by calculating the number of complementary health information technologies that are adopted by each hospital, excluding those that comprise the EMR, as reported in the database. Our literature review identified 52 HIT applications that are commonly used in hospitals and for which HIMSS Analytics captures data. These technologies were chosen because they are a part of the suite of clinical and administrative technologies used in hospitals and often discussed in conjunction with EMRs (Nenonen and Nylander 2002). The *HITC* measure is the sum of HIT applications implemented of the 52 HIT applications during the timeframe referenced.

We control for the type of hospital (*TEACH*) by classifying a hospital as a teaching/research hospital (1) or not (0). We also control for resource characteristics by including the hospital's profit versus not-for-profit status (*PROFIT*), (1) or not (0), and IS budget (*IS BUDGET*), "on a scale from 1 to 10, with 1 representing "under 1%" and increasing incrementally to 10, which represents "over 6%." Finally, we include *HITINIT* because of the recognition that U.S. states vary in the extent to which they promote HIT adoption both through legislation and private and public initiatives. States have different laws related to EMRs—such as privacy protection—that have been implicated in prior work as a cause of network effects (Miller and Tucker 2009). Therefore, we control for these environmental influences by including a continuous variable that is a count of the number of HIT initiatives underway within each state at the time this research was conducted (*HITINIT*) (Angst et al. 2006).

Though recent work by Miller and Tucker (2009) finds that there are network benefits associated with EMR adoption, we exclude any explicit costs and benefits in our model and operationalization. This decision is based on two considerations. One is rooted in social contagion theory, which notes that uncertainties (in this case regarding cost and benefits) lead firms to seek information from others about the true value of adoption. A second reason for exclusion is that even among the adopters, the true costs and benefits of EMR adoption are as yet unknown (Hillestad et al. 2005).

5. Results and Discussion

5.1. Sample Size and Computational Requirements

We used the mhdiff macro (Strang 2001) for SAS (SAS Institute, 2008, Version 9.2, 64 bit) on a Linux platform with Sun architecture. The high-performance computing machine consisted of two quad-core AMD processors (eight cores) with 32 GB of RAM available for processing. Initially we used all 3,989 hospitals in the analysis. Because the distance calculation requires pairwise comparison, this yielded a matrix of Euclidian distances that was 3,989 by 3,989. Taken together, the size of the data set, the complexity of the model, and the iterative nature of maximum likelihood estimation (MLE) did not allow us to fit the models to the full data set (the multiple models running exhausted system resources after more than 420 hours). We incrementally increased the random selection of hospitals and determined that even a 10% sample yielded robust coefficients, but up to a 50% sample could be run (taking approximately 119 hours to complete). Necessary computational time increased exponentially with increases in sample size; thus, we ultimately settled on a 40% sample that allowed convergence of most models within 24–48 hours' time. We present descriptive statistics for the entire sample and U.S. geographic regions in Table 2.

5.2. Model Fit

Although, in the general linear model, the proportion of variance that is accounted for in the dependent variable by one or more explanatory/predictor variables is a useful measure of overall fit, "variance accounted for" measures are not good indices when working with generalized MLE models (Cohen et al. 2003, p. 503). Nonetheless, it is valuable to quantify the explanatory power of one model as compared with another. We report three such measures, but caution the reader that these measures are estimates whose properties are not well known.

Using an analogy in an MLE context between the proportional reduction in the deviance (i.e., $-2 \times$ log likelihood of a fitted model) between a richer and a simpler model, Menard (2002, p. 24) shows the formulation for a likelihood ratio pseudo-R^2, which we denote R_L^2. An alternative to R_L^2 is the Cox and Snell pseudo-R^2, which we denote by R_{CS}^2, and it is another way of quantifying the difference between a more complex and simpler model. However, R_{CS}^2 does not have a maximum value of 1, and thus it is not on

Table 2   Descriptive Statistics for Full Sample and by U.S. Regions

| | Descriptives: Mean ± std. dev. or count (% of total) | | | | | |
Variable	All	NE	MW	South	West	Description
HOSPITALS	3,989	641	1,056	1,571	720	Number of hospitals
HITC	34.43 ± 6.56	34.82 ± 5.09	32.99 ± 7.36	35.35 ± 6.31	34.17 ± 6.64	Concentration of HIT apps
PROFIT	665 (16.7%)	61 (9.5%)	120 (11.4%)	371 (23.6%)	113 (15.7%)	*For-profit* variable
TEACH	334 (8.4%)	121 (19.2%)	80 (7.6%)	88 (5.6%)	43 (6.0%)	Academic or not
HITINIT	16.74 ± 14.47	23.81 ± 14.47	16.24 ± 12.57	9.15 ± 3.46	27.72 ± 20.63	State HIT initiatives
IS BUDGET	2.84 ± 3.04	2.76 ± 2.60	3.07 ± 3.24	2.71 ± 3.01	2.85 ± 3.14	Percentage of budget for IS (scale from 1 to 10)[a]
SIZE	183.31 ± 163.62	229.35 ± 172.85	168.09 ± 167.28	180.84 ± 164.06	170.23 ± 140.04	Number of staffed beds
AGE	29.37 ± 34.09	38.35 ± 43.01	33.14 ± 36.27	24.18 ± 28.19	27.12 ± 31.19	When hosp. opened relative to 2005 (2001 is four years)
AGE × *SIZE*	6,635 ± 12,667	9,329 ± 14,616	6,820 ± 13,172	5,734 ± 11,987	5,933 ± 11,075	Number of staffed beds × age of hospital
WIRED[b]	0.24 ± 1.03	0.36 ± 1.40	0.23 ± 0.98	0.18 ± 0.80	0.15 ± 0.78	Number of times on Most Wired list in past seven years

[a]The mean of 2.84 falls into 1.5%–1.99% of total budget range.

[b]Although the award is entitled "The 100 Most Wired Hospitals," the total count on average exceeds 100 hospitals per year. This occurs for two reasons: (1) more than 100 hospitals made the list because of statistical ties, and/or (2) a health system, or a portion of a health system that includes multiple hospitals, was given the award.

a 0–1 scale as traditional R^2 measures. Nagelkerke (1991) modifies the Cox and Snell pseudo-R^2 so that its maximum is 1, placing it back onto the familiar scale, which we denote by R_N^2. Although we find R_L^2 and R_N^2 to be most useful for comparison, we report the Cox and Snell pseudo-R^2 for completeness. Finally, we also include the Akaike Information Criterion (AIC) as a way to compare nonnested models. The AIC is defined as the model of interest's deviance with a penalty factor of twice the number of model parameters, divided by the sample size (i.e., AIC = $(Deviance + 2m)/n$, where m is the number of fitted parameters and n is the sample size) (e.g., Cohen et al. 2003).

Based on the results of the bivariate correlation analysis (see §EC.2 in the e-companion) and the relatively low correlations, we do not anticipate multicollinearity to be a problem. Model estimation results for the 40% sample are shown in the seventh column of Table 3. We first include control variables in the model (third column), followed by the heterogeneous diffusion predictors (fourth through seventh columns). Such a sequential analysis allows us to compare fit in the nested models and examine variance explained as more contagion factors are entered. An added benefit of this sequential process is that insights can surface with respect to the behavior of coefficients as new variables are added in different parts of the model. Because we have no a priori reason to conclude that one factor should be entered prior to another, we alternate the order of entry between susceptibility and infectiousness and report the differences and cumulative effect.

As shown in Table 3, each cumulative addition yields improvements in model fit and variance

explained. Most of the propensity factors are consistent across models. However, the effects of both *SIZE* and *AGE* change from being negative and significant in the propensity term to being nonsignificant in the full model. Of the social contagion factors, proximity contributes the most explanatory power, although each set of predictors explains significant variance above and beyond the propensity factors (for simplicity, we discuss only the Nagelkerke R^2: $R_{N\_Prx}^2 = 0.180$; $R_{N\_Prx\_Sus}^2 = 0.273$; $R_{N\_Prx\_Inf}^2 = 0.298$; $R_{N\_Prx\_Sus\_Inf}^2 = 0.312$; $R_{N\_All}^2 = 0.473$). The change in chi-squared relative to the baseline propensity model and the full model shows a significant improvement with each additional factor. Because both susceptibility and infectiousness are nested within the full model, we can compare their chi-squared values and find that there is a smaller difference in chi-square between infectiousness and the full model ($\Delta\chi^2 = 343.77$) than between susceptibility and the full model ($\Delta\chi^2 = 388.32$). This suggests that the infectiousness factor contributes greater explanatory power than the susceptibility factor. Finally, we note that the pseudo-R^2 measures are quite variable. Cohen et al. (2003) point out that there can be substantial variability in the "variance accounted for" measures, even for models as straightforward as logistic regression. Nonetheless, the omnibus effect sizes each attempt to convey an overarching model fit metric, which, despite its limitations, is valuable.

5.3. Hypothesis Tests

Among the control variables, *HITC*, *PROFIT*, *TEACH*, and *IS BUDGET* are significant, and *HITINIT*, *SIZE*, and *AGE* are not significant. The Northeast region of

Table 3   Sequential Heterogeneous Diffusion Model Results and Fit Indices for U.S. Hospitals

Variable	Variable type	Propensity (controls)	Propensity and susceptibility	Propensity and infectiousness	Propensity, susc., and inf.	Propensity and all contagion	Description
Hospitals	Count	1,583	1,583	1,583	1,583	1,583	
Propensity constant	Propensity (control variables)	−10.039*** (0.501)	−10.850*** (0.604)	−12.549*** (0.594)	−11.775*** (0.645)	−13.042*** (0.688)	Constant
HITC		0.170*** (0.012)	0.171*** (0.013)	0.168*** (0.013)	0.165*** (0.013)	0.191*** (0.014)	Concentration of HIT apps
PROFIT		−0.299† (0.192)	−0.548* (0.231)	−0.695** (0.228)	−0.611** (0.230)	−0.411† (0.233)	*For-profit* variable
TEACH		0.153 (0.212)	0.235 (0.228)	0.323 (0.222)	0.276 (0.228)	0.487* (0.224)	Academic or not
HITINIT		0.0017 (0.0038)	−0.0043 (0.0043)	−0.0025 (0.0043)	−0.0036 (0.0044)	−0.0061 (0.0044)	State HIT initiatives
IS BUDGET		0.035† (0.019)	0.057** (0.021)	0.057** (0.021)	0.065** (0.021)	0.069*** (0.020)	Percentage of budget for IS (scale from 1 to 10)
SIZE		−0.0019** (0.0006)	−0.0027* (0.0012)	−0.0013† (0.0007)	−0.0021† (0.0012)	−0.0017 (0.0013)	Number of staffed beds
AGE		−0.0098** (0.0031)	−0.0113* (0.0048)	−0.0131*** (0.0031)	−0.0040 (0.0050)	0.0037 (0.0054)	When hosp. opened relative to 2005 (2001 = 4)
NE region		0.449* (0.198)	0.593** (0.216)	0.463* (0.216)	0.555† (0.217)	0.521* (0.201)	Dummy variable if hospital in NE region
MW region		−0.155 (0.186)	−0.050 (0.199)	−0.062 (0.199)	−0.037 (0.200)	−0.236 (0.232)	Dummy variable if hospital in MW region
South region		0.044 (0.162)	−0.090 (0.180)	−0.026 (0.180)	−0.041 (0.180)	−0.098 (0.211)	Dummy variable if hospital in South region
Susceptibility constant	Susceptibility		0.0030 (0.0020)		0.018 (0.030)	0.039 (0.030)	Constant
SIZE			0.000013† (0.000007)		0.000009† (0.000005)	0.000023** (0.000007)	Number of staffed beds
AGE			0.000268*** (0.000038)		0.00022*** (0.00004)	0.000097* (0.000048)	When hosp. opened relative to 2005 (2001 = 4)
AGE × SIZE			−0.000001*** (0.00000)		−0.000001*** (0.00000)	−0.000001* (0.00000)	Number of staffed beds × age of hospital
WIRED	Infectiousness			0.032* (0.015)	0.029* (0.015)	0.032* (0.016)	Number of times on Most Wired list in past 7 yrs
SIZE				−0.000068* (0.000035)	−0.000051 (0.000154)	−0.00020† (0.00011)	Number of staffed beds
AGE				−0.00183** (0.00035)	−0.00210** (0.00060)	−0.00222** (0.00066)	When hosp. opened relative to 2005 (2001 = 4)
AGE × SIZE				0.000010*** (0.000002)	0.000011*** (0.000003)	0.000012*** (0.000003)	Number of staffed beds × age of hospital
Impact of distance	Spatial proximity (distance)					−0.000000 (0.000001)	Distance in miles from focal hospital
HEALTHSYS	Social proximity					10.165*** (0.496)	System influence: adoption by in-system hospital
Deviance test	Baseline model	3,315.62	2,884.77	2,884.77	2,884.77	2,884.77	Calculations for model fit
	Model as tested	3,043.55	2,473.97	2,429.41	2,404.48	2,085.64	
Log likelihoods	Baseline model	−1,657.81	−1,442.38	−1,442.39	−1,442.39	−1,442.39	
	Model as tested	−1,521.77	−1,236.98	−1,214.71	−1,202.24	−1,042.82	
	Likelihood ratio	272.07	410.80	455.36	480.29	799.13	
Fit indices	R^2_L	0.082	0.142	0.158	0.166	0.277	Comparison tests for model fit
	R^2_{CS}	0.158	0.229	0.250	0.262	0.396	
	R^2_N	0.180	0.273	0.298	0.312	0.473	Note: For better fitting models, R^2 values
	AIC	0.877	1.570	1.542	1.527	1.325	should increase as
	$\Delta\chi^2$ relative to propensity	—	569.58 df = 4, $p < 0.001$	614.14 df = 4, $p < 0.001$	639.07 df = 8, $p < 0.001$	957.91 df = 10, $p < 0.001$	contagion factors are added, and AIC should
	$\Delta\chi^2$ relative to full model	957.91 df = 10, $p < 0.001$	388.32 df = 6, $p < 0.001$	343.77 df = 6, $p < 0.001$	318.84 df = 2, $p < 0.001$	—	decrease.

Note. df, Degrees of freedom.
$^\dagger p < 0.10$; $^* p < 0.05$; $^{**} p < 0.01$; $^{***} p < 0.001$ (standard error).

the United States differs significantly from the West, whereas the MW and South do not differ from the West significantly.

H1A and H1B posited a positive relationship between a nonadopter hospital's age and size and the hospital's susceptibility to prior adoptions, respectively. The coefficients for both predictors are positive and significant in the full model for the susceptibility vector; thus, H1A and H1B are supported. In H1C, we argued that hospital age would substitute for the effects of hospital size on its susceptibility (see Figure ec.3 in the e-companion). The significant negative interaction between *SIZE* and *AGE* provides support for H1C.[10]

The infectiousness exerted by prior adopters was attributed to celebrity status, hospital size, hospital age, and the interaction of age with size. In Table 3, we see a significant positive coefficient for *WIRED*, thereby supporting H2A. Arguing that larger hospitals are likely to be perceived as the harbingers of innovation, H2B posited a positive relationship between hospital size and its infectiousness. The coefficient for *SIZE* in the infectiousness vector is negative and not significant ($p < 0.10$); thus, H2B is not supported. In H2C, we predicted that hospital age would negatively contribute to its infectiousness; thus, younger hospitals are more infectious. The coefficient for *AGE* is negative and significant, supporting H2C. Finally, as argued in H2D, hospital size and hospital age interact in contributing to a hospital's infectiousness. Although there is a significant positive relationship for the *AGE* × *SIZE* interaction, supporting H2D, the interpretation and effect of this is somewhat complex, so it is discussed in greater detail below.

The results for physical and social proximity (H3A and H3B, respectively) are mixed. We argued that spatially proximate adopters exert greater influence than those adopters that are farther away from the focal hospital. The coefficient for spatial proximity is nonsignificant; thus, H3A is not supported. In H3B, the presence of an adopter that is socially more proximate, i.e., belongs to the same health system, was posited to be more influential than an adopter outside of one's health system. The coefficient for social proximity is highly significant, supporting H3B.

5.4. Post Hoc Regional Analyses

The dummy variables for *REGION* included in the full analyses suggested significant differences across the four regions of the United States. To explore these differences further, we divided the sample by region (including all hospitals in the region) and estimated the full model separately for each region. Table 4 presents the regional results, juxtaposed with the 40% sample results used for the hypothesis tests from Table 3.

Some differences among regions are evident, particularly with respect to the NE and West. Of note is the effect of celebrity hospitals: in the NE, which has almost double the number of *WIRED* facilities relative to the other regions, this variable is not significant, whereas in the other three regions it is. Additionally, distance is significant only in the MW and West, where population density is lower, with adoption by closer entities being more influential than distal adoptions.[11]

5.5. Discussion

In this study we sought to understand the dynamics of contagion with respect to the adoption of EMR technology in U.S. hospitals. The contagion lens explicitly acknowledges the mutual influence that organizations exert on each other within an institutional field. We proposed hypotheses explicating the drivers of a nonadopting hospital's susceptibility to influence, the infectiousness of an adopter, and the effects of social and spatial proximity to adopters on a nonadopting hospital's likelihood of adoption. Results confirm seven of the nine hypotheses. The two that were contrary to predictions relate to the theorized positive effects of hospital size for infectiousness (negative at $p < 0.10$) and the influence of spatial proximity to adopting hospitals. The full model explains a substantial proportion of variance ($R_N^2 = 18\%$ versus 47%) in a hospital's likelihood of adopting EMRs. Therefore, it is clear that the contagion perspective offers a powerful and rich lens through which to understand and predict how EMR technology is likely to diffuse across U.S. hospitals. Possibly even more noteworthy is that the inclusion of the contagion factors had a major effect on variance explained over the propensity model ($R_N^2 = 18\%$ versus 47%). Although the effect size of some of the contagion variables is relatively small, we note that the value reported is a per-period increase (or decrease) and the effect is cumulative in subsequent periods. In addition, the effects of the individual variables within and across factors are additive, except where interaction terms include both variables.

One plausible explanation for the nonsignificance of distance in the full national sample is that with

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[10] Podsakoff et al. (1996, p. 281) note that for two variables to act as substitutes, their main effects must be significant in the same direction, and the interaction of the two must be in the opposite direction of the two main effects.

[11] The population density for U.S. Census regions is as follows: the Northeast has 339 people per square mile, the South has 128, the Midwest has 88, and the West has 40. See U.S. Census Bureau (2008).

Table 4   **Results Presented by Region of U.S. and Summary Interpretations**

Variable	All regions	Brief interpretation[a]	NE	MW	South	West
Propensity constant	−13.042*** (0.688)	Baseline propensity	−14.983*** (1.333)	−13.777*** (0.900)	−12.598*** (0.772)	−14.083*** (1.257)
HITC	0.191*** (0.014)	A hospital that has 1 more HIT application than another hospital is 21% more likely to adopt an EMR	0.245*** (0.029)	0.204*** (0.019)	0.164*** (0.015)	0.190*** (0.028)
PROFIT	−0.411[†] (0.233)	Not-for-profit hospitals are 34% more likely to adopt than for-profit hospitals	−0.852* (0.403)	0.603[†] (0.317)	−0.014 (0.215)	−0.649[†] (0.338)
TEACH	0.487* (0.224)	Academic/teaching hospitals are 63% more likely to adopt than other hospitals	−0.466 (0.300)	−0.475 (0.321)	−0.053 (0.267)	0.779* (0.382)
HITINIT	−0.0061 (0.0044)	The number of HIT initiatives in a state is not predictive of EMR adoption	0.002 (0.008)	−0.031** (0.009)	0.004 (0.020)	0.004 (0.005)
IS BUDGET	0.069*** (0.020)	A hospital that devotes 0.5% more of its budget to IS relative to another hospital is 7% more likely to adopt	0.117*** (0.030)	0.090** (0.035)	−0.021* (0.024)	0.104*** (0.030)
SIZE	−0.0017 (0.0013)	Size is not significant in the full model, but is negative and significant in the absence of contagion factors	−0.0012 (0.0015)	0.0030[†] (0.0013)	0.0022[†] (0.012)	−0.003 (0.002)
AGE	0.0037 (0.0054)	Age is not significant in the full model, but is negative and significant in the absence of contagion factors	−0.0054 (0.0073)	0.001 (0.007)	0.014* (0.007)	0.012 (0.009)
Susceptibility						
Susceptibility constant	0.039 (0.030)	Baseline susceptibility	−0.036 (0.102)	0.083* (0.035)	−0.112*** (0.027)	0.032 (0.076)
SIZE	0.000023** (0.000007)	Larger hospitals are more susceptible to influence than smaller; One standard deviation change in size (±163.32 beds) results in less than 1% increase in susceptibility	0.000054[†] (0.000030)	−0.000019 (0.000027)	0.000021* (0.000010)	0.000057[†] (0.000034)
AGE	0.000097* (0.000048)	Older hospitals are more susceptible to influence than younger; One standard deviation change in age (±34.09 years) results in less than 1% increase in susceptibility	0.00038* (0.00017)	0.00054*** (0.00014)	0.000095* (0.00004)	0.00018 (0.00020)
AGE × SIZE	−0.000001* (.00000)	As SIZE increases, the contagious effect of increased AGE, decreases. If both SIZE and AGE increase 1 std. dev., contagion drops 1.3%	−0.000001* (0.00000)	−0.000001* (0.000001)	−0.000000 (0.00000)	−0.000001[†] (0.000001)
Infectiousness						
WIRED	0.032* (0.016)	A hospital with one more Most WIRED awards than another hospital is 3.3% more infectious (influential)	0.025 (0.027)	0.056* (0.029)	0.151*** (0.033)	0.066[†] (0.040)
SIZE	−0.00020[†] (0.00011)	Hospital size is unrelated to infectiousness, except in the MW and South regions, where smaller hospitals are more infectious	−0.00030 (0.00038)	−0.00053** (0.00017)	−0.00029** (0.00012)	−0.00057 (0.00043)

Table 4   **(Continued)**

Variable	All regions	Brief interpretation[a]	NE	MW	South	West
AGE	−0.00222** (0.00066)	Younger hospitals are more infectious (influential) than older hospitals; a hospital that is 1 standard deviation younger is about 7.3% more infectious	−0.00173[†] (0.00103)	−0.00423** (0.00136)	−0.00155* (0.00079)	−0.00351* (0.00172)
AGE × SIZE	0.000012*** (0.000003)	Older, larger and younger, smaller hospitals are significantly more infectious than older, smaller and younger, larger hospitals; influence increases by 16.4% when *SIZE* and *AGE* vary by 1 std. dev.	0.000015*** (0.000004)	0.000026*** (0.000008)	−0.000003 (0.000004)	−0.000008 (0.000009)
		Social and spatial proximity				
Impact of distance	−0.000000 (0.000001)	Distance from an adopter does not influence adoption, except in the MW and West where closer provide more influence.	−0.000009 (0.000023)	−0.000037[†] (0.000021)	−0.000001 (0.000004)	−0.000007** (0.000002)
HEALTHSYS	7.950*** (0.373)	An adoption by an in-system hospital is 2,835 times more influential to a non-adopter in that health system than an out-of-system hospital adoption.	6.487*** (0.421)	8.131*** (0.430)	6.722*** (0.307)	7.831*** (0.374)
		Model fit				
Dev. baseline	2,884.77	Model fit varies between	1,334.84	1,683.99	1,889.94	1,431.52
Dev. model	2,085.64	regions with the West	870.52	1,075.74	1,314.46	731.11
LL baseline	−1,442.39	providing the best fit.	−667.42	−842.00	−944.970	−715.76
LL model	−1,042.82		−435.26	−537.87	−657.230	−365.55
LL ratio	799.13		464.32	608.25	575.48	700.41
R^2_L	0.277	Variance explained varies	0.348	0.361	0.304	0.489
R^2_{CS}	0.396	between regions with the	0.515	0.438	0.307	0.622
R^2_N	0.473	West providing the most explained variance.	0.589	0.549	0.438	0.721

Note. LL, Log likelihood.

[a]The interpretation described is referencing the coefficients for the full 40% random sample unless otherwise noted.

[†]$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (standard error).

the widespread availability of real-time, rich information facilitated by the Internet, distance is becoming increasingly irrelevant as a constraint on access to knowledge about the actions of peer firms within an industry. We argued that physical proximity matters because of the existence of localized knowledge spillovers. To the extent that such knowledge can now be obtained through other channels, this attenuates the importance of being physically close to adopter hospitals. Our regional analyses indicated that hospitals in areas with relatively lower population density (MW and West) are significantly influenced by proximate adopters, whereas those in more densely populated areas (NE and South) are not. This is consistent with the LKS argument: lower population density increases the likelihood of competition for knowledge workers and associated knowledge transfer across hospitals.

With respect to the role of size in infectiousness, we find that although the negative relationship is not statistically significant in the national sample ($p < 0.10$), there are significant regional differences. Interestingly, smaller-size hospitals are more infectious in the South and Midwest, two regions with moderate population density compared to the West and Northeast. The coefficient of variation for hospital size and corresponding 95% confidence interval limits (in parentheses) (e.g., Kelley 2007) for the MW, South, West, and NE are 1.00 (0.93, 1.07), 0.91 (0.86, 0.96), 0.82 (0.76, 0.89), and 0.75 (0.70, 0.82), respectively. The fact that the coefficient of variance is significantly larger in the MW compared to both the NE and West (because the confidence intervals do not overlap), and the South compared to the NE, may help to explain regional differences, thereby causing variability relative to mean size to become a more salient factor in managerial attention.

Further reflection suggests several additional reasons why smaller hospitals might be more infectious. Some have noted that larger and more well-established firms look to smaller, more agile firms to test proof of concept and experiment with innovations. These large, richly connected firms have little trouble observing these pilot tests because consultants, vendors, and analysts are quick to point out the benefits (Lieberman and Asaba 2006). Thus, a non-adopter hospital may believe that EMR adoption by a smaller hospital reflects the growing importance of the technology for future medical practice. A second explanation may be that when a large urban hospital adopts, no one notices, but when a small rural hospital adopts, it is big news.[12] Thus, to the degree that smaller adopter hospitals are perceived to be nimble pioneers and at the leading edge, ceteris paribus, their behavior is more likely to be noticed and emulated.

In an effort to more fully understand the interaction term's significance in H2D, and because the hypothesized main effect of size was not confirmed to be positive or significant in H2B, we graphed the interaction results holding the *WIRED* value constant while varying *SIZE* and *AGE* (see Figure ec.4 in the e-companion). From this graph it is apparent that when size and age are at opposite extremes, a hospital is less desirable as a role model. Thus, the adoption of EMRs by young and large or old and small hospitals exerts almost no infectious influence on potential adopters, whereas adoption by large, old hospitals is the most contagious.

An important finding of the study is that many of the intrinsic firm characteristics or "propensity" factors either diminish in significance as predictors, or their effects change substantially when the contagion factors are added to the model. Thus, our results suggest that variables that frequently appear in firm-level research, such as size and age, are more appropriately modeled within the contagion terms than as noncontagious predictors. It is also noteworthy that the same set of hospital characteristics—its size and age—plays a significantly different role in adopter and nonadopter hospitals.

6. Limitations of the Research

Prior to discussing the implications of our findings, we acknowledge the limitations of the research that represent fruitful areas for extension. In our empirical analysis we use a dichotomous variable for EMR adoption that may artificially inflate diffusion. Some hospitals may own EMRs but not use them, or use them to varying degrees. However, usage data is typically hard to obtain, specifically in the early years of

the diffusion of an innovation, as is the case with this study. Future studies in this domain could focus on investigating the "assimilation gap" for EMR systems (Fichman and Kemerer 1999).

Because of the computing constraints we discussed, we reduced the sample size to a 40% random selection and also conducted regional analyses. However, even with a 10% random selection, the results were consistent except that the weaker coefficients approached insignificance or became insignificant, suggesting that the findings are robust.

We also note that our measure for celebrity firms was not as complete as the other variables in the study in that the Most Wired list was not published prior to the year 1999. Although it is not uncommon in event studies to have new information enter the population during the timeframe under investigation, it is methodologically challenging to appropriately account for this influence. Thus, although the impact of the variable *WIRED* does not take effect until after 1999, there is the possibility that empirically its effect would have been noted earlier if the infectious hospital adopted its EMRs before 1999. In only 36 cases (out of 298 unique hospitals awarded) did a hospital on the Most Wired list adopt prior to 1999. We would also suggest that the same characteristics that subsequently led to being named Most Wired were present in years prior to the award, and therefore would have contributed to the hospital's infectious status.

Although we included a rich set of contagion-related variables as predictors for modeling the diffusion of EMRs, our theoretical stance naturally precluded other potentially relevant covariates. For example, we were not able to tap into any management-level data such as the propensity to innovate or other aspects of the hospitals, such as their decision-making model (e.g., centralized, decentralized, federal, etc.). Such variables could be included in future investigations of EMR adoption.

In an effort to reduce complexity in our model, we simplified the influence of contagion. We acknowledge that prior research alludes to it acting in a more prescriptive way. For example, Strang and Macy (2001) suggest that contagion is stronger among peers such that firms of similar characteristics tend to mimic each other to a greater extent than dissimilar firms. Although this is an interesting avenue to pursue in future work, there are significant empirical challenges associated with a model that would take into consideration large size or age differentials and the associated influence of contagion.

Finally, with respect to the findings related to health-system membership, our theoretical logic was constructed around a direct contagion effect. Although contagion through a social network such as

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[12] We thank the associate editor for highlighting this potential explanation.

a health system is a likely means of spreading innovations, an alternative argument is that even in the absence of contagion, initiatives by the parent organization are likely to spread within the network. Furthermore, the network externalities are likely to be greater within a system rather than across systems. We have considered this confound, but a remedy for isolating these effects is not obvious and requires future investigation.

7. Implications and Conclusions

7.1. Implications for Research

There are several theoretical implications of this research, some of which challenge conventional wisdom, whereas others offer opportunities for future research. We first discuss the implications of the regional analysis, and next those relationships for which alternative theoretical framing offers contradictory propositions.

The variation in our results by region suggests a need to more closely consider the implications of generalizing findings of region-based studies to a broader population. Though we speculated that population density and variability in hospital size are potential drivers of regional variations, further research needs to investigate this question in more detail before any definitive conclusion can be reached. As noted earlier, we found that proximity matters in areas where institutions are sparse, and size matters for infectiousness when there is more variation in hospital size. The implications for theory are that there would appear to be geographic covariates that impact social contagion among organizations and the diffusion of innovations. Beyond sheer density, there may be organizations such as industry associations and trade groups that play a role in the contagion process by reducing the uncertainty associated with the innovation. Along the same lines of reasoning, LKS may be occurring between firms *across* industries, especially in regions where hospitals do not have close peer organizations. As Gaba and Meyer (2008) note, cross-population linkages can enable organizations to learn from those in other business sectors. Finally, because our definitions of regions are somewhat broader, we expect that a more nuanced regional analysis would provide additional insight into the dynamics of social contagion.

As Greve (2005) points out, the finding that maturity (represented as greater size and age) positively influences susceptibility challenges conventional wisdom as espoused in the organizational ecology literature. We suggest that there is less contradiction in these conflicting findings than might appear to be on the surface, and that this may be a theoretical rather than empirical issue. From the organizational ecology perspective, mature firms have been shown to resist change, largely because of inertia in decision making and organizational action. Such a conceptualization of maturity is arguably one that assesses a static propensity rather than a factor in a dynamic social contagion process. In contrast to a view that size and age are impediments in innovation because they create apathy in organizations, maturity provides more opportunities for learning from others. We also underscore an important implication of our results: the interpretation of coefficients in the absence of a fully specified model with variables appropriately located could lead to possibly erroneous conclusions.

Our sequential analysis with nested models allowed us to gain insights about the impacts of each of the contagion factors. In particular, our study again underscored the importance of social relationships in firm behaviors, suggesting that investigations of innovation adoption that ignore such intrapopulation linkages are likely to be incomplete. We found that social proximity in the form of membership in a health system was by far the strongest predictor of adoption. In addition, we show that infectiousness is stronger than susceptibility, suggesting that at a population level, the characteristics of a nonadopter, although important, are not as critical as the attributes of the spreaders in the social ecosystem. Future studies could likewise focus on improving understanding of the relative effects of different sets of variables in the contagion process.

Findings from this study reinforce the importance of theorizing about and including interactions in examinations of social contagion. Others have noted that this is a relatively underexplored area of contagion research that merits further work (e.g., Wejnert 2002). We included interactions among *SIZE* and *AGE* as susceptibility and infectiousness factors, but other moderating influences are plausible as well. For example, it may be the case that the effects of social proximity are accentuated in the presence of physical proximity. Or that the two act as substitutes in their effects on likelihood of adoption. A similar effect may be envisioned across infectiousness and proximity covariates, viz., spatially or socially proximate role models are more influential than those that are further "away." Although methodologically challenging, future research could enrich contagion models by including a broader set of interactions.

A significant theoretical implication of our research relates to the conceptualization of "celebrity." Prior research has utilized multiple characteristics to identify role models within a population of firms (see Still and Strang 2009 for a recent review) with an underlying theoretical assumption that the actions of celebrities get more noticed than those of others. However, very few studies have investigated the underlying microprocesses of influence transfer. In other words,

is it learning, imitation, or some other mechanism that is responsible for the observed effects of celebrity firms? This question merits further research.

Finally, this study used the social contagion lens to study the diffusion of EMRs. Although results show that such a conceptualization explains significant variance in a hospital's likelihood of adoption, there are nevertheless other rival theoretical perspectives that could be deployed to understand why there are differences in the speed with which hospitals adopt an innovation such as an EMR. For instance, some literature argues that firms adopt innovations as a result of it becoming "fashionable" (Abrahamson and Fairchild 1999). Furthermore, although we implicated observation and information transmission as the mechanism underlying social influence, our data are not granular enough to distinguish between learning by observation, knowledge transfer, or a purely imitative learning. Future research can explore alternative theoretical perspectives as well as different research designs that use in-depth, qualitative analyses to isolate specific learning processes.

7.2. Implications for Practice

As just noted, the influence exerted by adopters is an important aspect of diffusion. To the degree that EMR diffusion is beneficial for society, several policy interventions are available that can accelerate social contagion and encourage wider adoption. First, our findings suggest that the population could be "seeded" with influential hospitals. This has already been done to an extent as evident by regional branches of highly acclaimed facilities (i.e., Mayo Clinic sites in Phoenix, Arizona; Jacksonville, Florida; and Rochester, Minnesota). Second, granting organizations could offer funds targeted for distribution in strategic, regional locations. Third, although we operationalized celebrity status using the Most Wired list, other forms of celebrity are likely to exist and, in fact, this may be a recursive relationship such that celebrity firms are more likely to be *WIRED*, and being *WIRED* further reinforces their celebrity status. More importantly, this simply demonstrates that influential hospitals exist and they should continue to be acknowledged, be it through awards or public announcements. It is also important to recognize that these influences are likely to vary regionally. Finally, with the recent move toward transparency of information in health care, it is possible that metrics such as quality of care and patient perceptions of care will become salient drivers of infectiousness such that better performing hospitals will become role models for others. Thus, policy intervention to ensure that such hospitals adopt EMRs early could increase the rate at which contagion spreads.

We find that hospitals that are older and larger in size are more likely to "notice" environmental events such as increasing adoption of EMRs by others within their ecological system and, as a result, are more susceptible to social influence. The underlying conduits for this heightened environmental sensitivity are simply more proactive scanning and denser social relationships beyond firm boundaries. Scanning and relationship building represent actionable managerial interventions that can be proactively orchestrated even in smaller and younger organizations. In other words, to the degree that greater noticing contributes to better information, managers can devise strategies and structures to facilitate this. For example, greater organizational engagement in industry and professional associations and other similar forums will enhance the exposure of employees to trends and developments occurring industrywide. It is important to underscore, however, that the response to information gleaned through greater noticing needs to be thoughtful. Knowledge that a given technology is increasing in adoption among peer organizations must be juxtaposed with an internal assessment of the technology's fit with firm strategy, as well as rational evaluation of the extent to which the existing organizational context will allow the gains from the technology to be appropriated. In the absence of such reasoned trade-offs, organizations run the risk of succumbing to bandwagon effects (Abrahamson and Rosenkopf 1993) and may gain limited benefits from technology adoption.

7.3. Conclusion

The uptake of EMR systems, an important component of transforming health care in the United States, has been slow. First implementations date back to the early 1970s, yet growth has been stagnant, and only recently has it increased (Bower 2005). Bates (2000) suggests several reasons for the slow diffusion ranging from lack of evidence showing the impact of EMRs, to providers' fragmented internal structure, to poor funding for research, to lack of demand from the health-care industry, and finally to financial constraints. Yet, Bower (2005) notes that no studies have investigated the contagious spread of HIT at the firm or industry level. Our research addresses this gap and demonstrates that diffusion could be accelerated if specific attention is given to increasing social contagion effects. The social contagion perspective is important in this context in particular because the technology is complex and managers are seeking evidence from others that the rewards of adoption outweigh the risks. Although social contagion may plausibly be present in the case of noncomplex innovations as well, to the degree that the relative costs and benefits of such innovations are more easily evaluated by potential adopters, influence through observation and information transmission may be

less potent. This study yields important insights into what factors increase the likelihood of adoption of EMRs, which will not only be useful for practitioners, but will also offer researchers directions for future investigations.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

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References

Abrahamson, E., G. Fairchild. 1999. Management fashion: Lifecycles, triggers, and collective learning processes. *Admin. Sci. Quart.* **44** 708–740.

Abrahamson, E., L. Rosenkopf. 1993. Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion. *Acad. Management Rev.* **18** 487–517.

Acs, Z. J., D. B. Audretsch, M. P. Feldman. 1994. R&D spillovers and recipient firm size. *Rev. Econom. Statist.* **76** 336–340.

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Admin. Sci. Quart.* **45** 425–455.

Angst, C. M., A. Desai, J. Wulff. 2006. State-level HIT activity and themes. *CHIDS Res. Briefings* **1** 1–4.

Ash, J. S., D. W. Bates. 2005. Factors and forces affecting EHR system adoption: Report of a 2004 ACMI discussion. *J. Amer. Medical Informatics Assoc.* **12** 8–12.

Ash, J. S., M. Berg, E. Coiera. 2004. Some unintended consequences of information technology in health care: The nature of patient care information system related errors. *J. Amer. Medical Informatics Assoc.* **11** 104–112.

Ashforth, B. E., R. H. Humphrey. 1997. The ubiquity and potency of labeling in organizations. *Organ. Sci.* **8** 43–58.

Attewell, P. 1992. Technology diffusion and organizational learning: The case of business computing. *Organ. Sci.* **3** 1–19.

Bandura, A. 1977. *Social Learning Theory*. Prentice Hall, Englewood Cliffs, NJ.

BarNir, A., J. Gallaugher, P. Auger. 2003. Business process digitization, strategy, and the impact of firm age and size: The case of the magazine publishing industry. *J. Bus. Venturing* **18** 789–814.

Bates, D. W. 2000. Using information technology to reduce rates of medication errors in hospitals. *British Medical J.* **320** 788–791.

Bates, D. W. 2002. The quality case for information technology in healthcare. *BMC Med. Inform. Decision Making* **2** 1–9.

Bates, D. W., M. Ebell, E. Gotlieb, J. Zapp, H. C. Mullins. 2003. A proposal for electronic medical records in U.S. primary care. *J. Amer. Medical Informatics Assoc.* **10** 1–10.

Blau, J., K. Land, K. Redding. 1992. The expansion of religious affiliation: An explanation of the growth of church participation in the United States, 1850–1930. *Social Sci. Res.* **21** 329–329.

Bower, A. G. 2005. The diffusion and value of healthcare information technology. Report, RAND Health, Santa Monica, CA, 1–77.

Breschi, S., F. Lissoni. 2001. Knowledge spillovers and local innovation systems: A critical survey. *Indust. Corporate Change* **10** 975–1005.

Broadbent, M., P. Weill, D. St. Clair. 1999. The implications of information technology infrastructure for business process redesign. *MIS Quart.* **23** 159–182.

Brynjolfsson, E., L. M. Hitt. 2000. Beyond computation: Information technology, organizational transformation and business performance. *J. Econom. Perspect.* **14** 23–48.

Bush, G. W. 2004. President's State of the Union Address. January 20. Washington, DC.

Cacioppo, J. T., R. E. Petty, J. Sidera. 1982. The effects of salient self-schema on the evaluation of proattitudinal editorials: Top-down versus bottom-up message processing. *J. Exp. Soc. Psych.* **18** 324–338.

Castaldo, S. 2008. *Trust in Market Relationships*. Edward Elgar Publishing, Northampton, MA.

Chaudhry, B., J. Wang, S. Wu, M. Maglione, W. Mojica, E. Roth, S. C. Morton, P. G. Shekelle. 2006. Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Ann. Internal Medicine* **144** E12–E22.

Christensen, C. M., J. H. Grossman, J. Hwang. 2009. *The Innovator's Prescription: A Disruptive Solution for Health Care*. McGraw–Hill, New York.

Cohen, J., P. Cohen, S. G. West, L. S. Aiken. 2003. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed. Lawrence Erlbaum Associates, Mahwah, NJ.

Daft, R. L. 1978. A dual-core model of organizational innovation. *Acad. Management. J.* **21** 193–210.

Daft, R. L., K. E. Weick. 1984. Toward a model of organizations as interpretation systems. *Acad. Management Rev.* **9** 284–295.

Damanpour, F. 1987. The adoption of technological, administrative, and ancillary innovations: Impact of organizational factors. *J. Management* **13** 675–688.

Damanpour, F. 1991. Organizational innovation: A meta-analysis of effects of determinants and moderators. *Acad. Management J.* **34** 555–590.

Debruyne, M., D. J. Reibstein. 2005. Competitor see, competitor do: Incumbent entry in new market Niches. *Marketing Sci.* **24** 55–66.

Deephouse, D. 1996. Does isomorphism legitimate? *Acad. Management J.* **39** 1024–1039.

DesRoches, C., E. Campbell, S. Rao, K. Donelan, T. Ferris, A. Jha, R. Kaushal, D. Levy, S. Rosenbaum, A. Shields. 2008. Electronic health records in ambulatory care: A national survey of physicians. *New England J. Medicine* **359** 50–60.

Deutsch, M., H. B. Gerard. 1955. A study of normative and informational social influences upon individual judgment. *J. Abnormal Soc. Psych.* **51** 629–636.

Dewar, R. D., J. E. Dutton. 1986. The adoption of radical and incremental innovations: An empirical analysis. *Management Sci.* **32** 1422–1433.

DiMaggio, P., W. Powell. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *Amer. Sociol. Rev.* **48** 147–160.

Dobbin, F., L. Edelman, J. Meyer, W. R. Scott, A. Swidler. 1988. *The Expansion of Due Process in Organizations*. Ballinger, Cambridge, MA.

Doring, T., J. Schnellenbach. 2006. What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature. *Regional Stud.* **40** 375–395.

Elson, R. B., D. P. Connelly. 1995. Computerized patient records in primary care: Their role in mediating guideline-driven physician behavior change. *Arch. Family Medicine* **4** 698–705.

Federal Trade Commission and Department of Justice. 2004. Improving health care: A dose of competition. Report, Federal Trade Commission and Department of Justice, Washington, DC.

Fichman, R. G. 2000. *The Diffusion and Assimilation of Information Technology Innovations.* Pinnaflex Educational Resources, Cincinnati.

Fichman, R. G. 2001. The role of aggregation in the measurement of IT-related organizational innovation. *MIS Quart.* **25** 427–455.

Fichman, R. G. 2004. Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *J. Assoc. Inform. Systems* **5** 314–355.

Fichman, R. G., C. F. Kemerer. 1997. The assimilation of software process innovations: An organizational learning perspective. *Management Sci.* **43** 1345–1363.

Fichman, R. G., C. F. Kemerer. 1999. The illusory diffusion of innovation: An examination of assimilation gaps. *Inform. Systems Res.* **10** 255–275.

Fisher, E., D. Wennberg, T. Stukel, D. Gottlieb, F. Lucas, E. Pinder. 2003a. The implications of regional variations in medicare spending. Part 1: The content, quality, and accessibility of care. *Ann. Internal Medicine* **138** 273–287.

Fisher, E., D. Wennberg, T. Stukel, D. Gottlieb, F. Lucas, E. Pinder. 2003b. The implications of regional variations in medicare spending. Part 2: Health outcomes and satisfaction with care. *Ann. Internal Medicine* **138** 288–298.

Fombrun, C., M. Shanley. 1990. What's in a name? Reputation building and corporate strategy. *Acad. Management J.* **33** 233–258.

Gaba, V., A. Meyer. 2008. Crossing the organizational species barrier: How venture capital practices infiltrated the information technology sector. *Acad. Management J.* **51** 976–998.

Gioia, D. A. 1986. *Symbols, Scripts, and Sensemaking: Creating Meaning in the Organizational Experience.* Jossey-Bass, San Francisco.

Gostin, L. O., J. Hodge. 2002. Personal privacy and common goods: A framework for balancing under the national health information privacy rule. *Minnesota Law Rev.* **86** 1439–1479.

Gowrisankaran, G., J. Stavins. 2004. Network externalities and technology adoption: Lessons from electronic payments. *RAND J. Econom.* **35** 260–276.

Greatbatch, D. H., C. P. Campion, P. Luff. 1995. How do desk-top computers affect the doctor-patient interaction? *Family Practice* **12** 32–36.

Greve, H. 2005. Interorganizational learning and heterogeneous social structure. *Organ. Stud.* **26** 1025–1047.

Greve, H. 2009. Bigger and safer: The diffusion of competitive advantage. *Strategic Management J.* **30** 1–23.

Greve, H. R. 1995. Jumping ship: The diffusion of strategy abandonment. *Admin. Sci. Quart.* **40** 444–473.

Greve, H. R., D. Strang, N. B. Tuma. 1995. Specification and estimation of heterogeneous diffusion processes. *Sociol. Methodology* **25** 377–420.

Harrison, M., R. Koppel, S. Bar-Lev. 2007. Unintended consequences of information technologies in health care—An interactive sociotechnical analysis. *J. Amer. Medical Informatics Assoc.* **14** 542–549.

Hartley, C., E. Jones. 2005. *EHR Implementation: A Step-By-Step Guide for the Medical Practice.* American Medical Association, Chicago.

Haunschild, P. R., A. S. Miner. 1997. Modes of interorganizational imitation: The effects of outcome salience and uncertainty. *Admin. Sci. Quart.* **42** 472–500.

Haveman, H. A. 1993. Follow the leader: Mimetic isomorphism and entry into new markets. *Admin. Sci. Quart.* **38** 593–627.

Hillestad, R., J. Bigelow, A. G. Bower, F. Girosi, R. Meili, R. Scoville, R. Taylor. 2005. Can electronic medical record systems transform healthcare? An assessment of potential health benefits, savings, and costs. *Health Affairs* **24** 1103–1117.

HIMSS Analytics. The EMR adoption model. Accessed August 26, 2009, http://www.himssanalytics.org/docs/EMRAM_aH_corrected.pdf.

Holden, R. 1986. The contagiousness of aircraft hijacking. *Amer. J. Sociol.* **91** 874–904.

Howell, J., P. Dorfman, S. Kerr. 1986. Moderator variables in leadership research. *Acad. Management Rev.* **11** 88–102.

Huergo, E., J. Jaumandreu. 2004. How does probability of innovation change with firm age? *Small Bus. Econom.* **22** 193–207.

Jha, A., T. Ferris, K. Donelan, C. DesRoches, A. Shields, S. Rosenbaum, D. Blumenthal. 2006. How common are electronic health records in the United States? A summary of the evidence. *Health Affairs* **25** w496–w507.

Jha, A. K., C. M. DesRoches, E. G. Campbell, K. Donelan, S. R. Rao, T. G. Ferris, A. Shields, S. Rosenbaum, D. Blumenthal. 2009. Use of electronic health records in U.S. hospitals. *New England J. Medicine* **360** 1628–1638.

Kazley, A., Y. Ozcan. 2007. Organizational and environmental determinants of hospital EMR adoption: A national study. *J. Medical Systems* **31** 375–384.

Kelley, K. 2007. Sample size planning for the coefficient of variation: Accuracy in parameter estimation via narrow confidence intervals. *Behav. Res. Methods* **39** 755–766.

Kerr, S. 1977. Substitutes for leadership: Some implications for organizational design. *Organ. Admin. Sci.* **8** 135–146.

Knoke, D. 1982. The spread of municipal reform: Temporal, spatial, and social dynamics. *Amer. J. Sociol.* **87** 1314–1339.

Koppel, R., J. Metlay, A. Cohen, B. Abaluck, A. R. Localio, S. E. Kimmel, B. L. Strom. 2005. Role of computerized physician order entry systems in facilitating medication errors. *J. Amer. Medical Assoc.* **293** 1197–1203.

Lapointe, L., S. Rivard. 2005. A multilevel model of resistance to information technology implementation. *MIS Quart.* **29** 461–491.

le Bon, G. 1895. *The Crowd: A Study of the Popular Mind.* Viking Press, New York.

Lieberman, M., S. Asaba. 2006. Why do firms imitate each other? *Acad. Management Rev.* **31** 366–385.

Lorenzi, N. M., J. S. Ash, J. Einbinder, W. McPhee, L. Einbinder. 2005 *Transforming Health Care Through Information*, 2nd ed. Springer, New York.

Makoul, G., R. H. Curry, P. C. Tang. 2001. The use of electronic medical records: Communication patterns in outpatient encounters. *J. Amer. Medical Informatics Assoc.* **8** 610–615.

Mansfield, E. 1961. Technical change and the rate of imitation. *Econometrica* **29** 741–766.

March, J. G., J. P. Olsen. 1976. *Ambiguity and Choice in Organizations.* Universitetforslaget, Oslo, Norway.

Markle Foundation. 2004. Connecting Americans to their healthcare: Final report. Working Group on Policies for Electronic Information Sharing Between Doctors and Patients. Connecting for Health, Markle Foundation, New York.

Marsden, P. 1998. Memetics and social contagion: Two sides of the same coin. *J. Memetics, Evolutionary Mod. Info. Trans.* **2** 171–185.

Menard, S. 2002. *Applied Logistic Regression Analysis*, 2nd ed. Sage Publications, Thousand Oaks, CA.

Meyer, A. 1982. Adapting to environmental jolts. *Admin. Sci. Quart.* **27** 515–537.

Miller, A. R., C. Tucker. 2009. Privacy protection and technology diffusion: The case of electronic medical records. *Management Sci.* **55** 1077–1093.

Milliken, F. 1990. Perceiving and interpreting environmental change: An examination of college administrators' interpretation of changing demographics. *Acad. Management J.* **33** 42–63.

Myers, D. J. 2000. The diffusion of collective violence: Infectious-ness, susceptibility, and mass media networks. *Amer. J. Sociol.* **106** 173–208.

Nagelkerke, N. J. D. 1991. A note on a general definition of the coefficient of determination. *Biometrika* **78** 691–692.

Nenonen, M., O. Nylander. 2002. A theoretical framework for health information systems. *Intl. J. Healthcare Tech. Management* **4** 467–477.

Nohria, N., R. Gulati. 1996. Is slack good or bad for innovation? *Acad. Management J.* **39** 1245–1264.

Nord, W. R., S. Tucker. 1987. *Implementing Routine and Radical Innovation*. Lexington Books, Lexington, MA.

Ornstein, C. 2003. California hospital heeds doctors, suspends use of software. *Los Angeles Times* (January 22) B1.

Pan, E., D. Johnston, J. Adler-Milstein, J. Walker, B. Middleton. 2004. *The Value of Healthcare Information Exchange and Interoperability*. Center for Information Technology Leadership, Boston.

Paré, G., M. Trudel. 2007. Knowledge barriers to PACS adoption and implementation in hospitals. *Int. J. Medical Informatics* **76** 22–33.

Pilote, L., R. Califf, S. Sapp, D. Miller, D. Mark, W. Weaver, J. Gore, P. Armstrong, E. Ohman, E. Topol. 1995. Regional variation across the United States in the management of acute myocardial infarction. *New England J. Medicine* **333** 565–572.

Pisano, G., R. Bohmer, A. C. Edmondson. 2001. Organizational differences in rates of learning: Evidence from the adoption of minimally invasive cardiac surgery. *Management Sci.* **47** 752–768.

Podsakoff, P., S. MacKenzie, W. Bommer. 1996. Transformational leader behaviors and substitutes for leadership as determinants of employee satisfaction, commitment, trust, and organizational citizenship behaviors. *J. Management* **22** 259–298.

Podsakoff, P., S. MacKenzie, R. Fetter. 1993. Substitutes for leadership and the management of professionals. *Leadership Quart.* **4** 1–44.

Putnam, R. D. 1995. Bowling alone: America's declining social capital. *J. Democracy* **6** 65–78.

Rao, H., G. F. Davis, A. Ward. 2000. Embeddedness, social identity, and mobility: Why firms leave the NASDAQ and join the New York Stock Exchange. *Admin. Sci. Quart.* **45** 268–292.

Rindova, V., T. Pollock, M. Hayward. 2006. Celebrity firms: The social construction of market popularity. *Acad. Management Rev.* **31** 50–72.

Rogers, E. M. 1995. *Diffusion of Innovations*, 4th ed. The Free Press, New York.

Sambamurthy, V., A. S. Bharadwaj, V. Grover. 2003. Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quart.* **27** 237–264.

Sánchez, J. L., S. Savin, V. Vasileva. 2005. *Key Success Factors in Implementing Electronic Medical Records in University Hospital of Rennes*. L'Ecole Nationale de la Santé Publique (National School of Public Health), Rennes, Rennes, France.

Schmitt, K. F., D. A. Wofford. 2002. Financial analysis projects clear returns from electronic medical records. *Healthcare Financial Management* **56** 52–57.

Scott, J. T., T. G. Rundall, T. M. Vogt, J. Hsu. 2005. Kaiser permanente's experience of implementing an electronic medical record: A qualitative study. *British Medical J.* **331** 1313–1316

Simon, H. A. 1991. Bounded rationality and organizational learning. *Organ. Sci.* **2** 125–134.

Simon, S. R., R. Kaushal, P. D. Cleary, C. A. Jenter, L. A. Volk, E. G. Poon, E. J. Orav, H. G. Lo, D. H. Williams, D. W. Bates. 2007. Correlates of electronic health record adoption in office practices: A statewide survey. *J. Amer. Medical Informatics Assoc.* **4** 110–117.

Singer, J. D., J. B. Willett. 2003. *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press, New York.

Solovy, A. 2007. Ten lessons from the top 100: One thing is certain—Technology is part of the process of improving care. *Hospital Health Networks* **81** 40–63.

Soule, S. A., J. Earl. 2001. The enactment of state-level hate crime law in the United States: Intrastate and interstate factors. *Sociol. Perspect.* **44** 281–305.

Still, M., D. Strang. 2009. Who does an elite organization emulate? *Admin. Sci. Quart.* **54** 58–89.

Strang, D. 1995. Mhdiff: user documentation. Report, Cornell University, Department of Sociology, Ithaca, NY.

Strang, D. 2001. Mhdiff macro v2.1. Cornell University, Department of Sociology, Ithaca, NY.

Strang, D., M. W. Macy. 2001. In search of excellence: Fads, success stories, and adaptive emulation. *Amer. J. Sociol.* **107** 147–182.

Strang, D., S. A. Soule. 1998. Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Rev. Sociolgy* **24** 266–290.

Strang, D., N. B. Tuma. 1993. Spatial and temporal heterogeneity in diffusion. *Amer. J. Sociol.* **99** 614–639.

Suchman, M. 1995. Managing legitimacy: Strategic and institutional approaches. *Acad. Management Rev.* **20** 571–610.

Swanson, E. 1994. Information systems innovation among organizations. *Management Sci.* **40** 1069–1092.

Thomas, J., S. Clark, D. A. Gioia. 1993. Strategic sensemaking and organizational performance: Linkages among scanning, interpretation, action, and outcomes. *Acad. Management J.* **36** 239–270.

Tolbert, P., L. Zucker. 1983. Institutional sources of change in the formal structure of organizations: The diffusion of civil service reform, 1880–1935. *Admin. Sci. Quart.* **28** 22–39.

Tuma, N. B., M. T. Hannan. 1984. *Social Dynamics: Models and Methods*. Academic Press, Orlando, FL.

U.S. Census Bureau. 2008. Population estimates: Population density for States and Puerto Rico: July 1, 2008. Accessed August 30, 2009, http://www.census.gov/popest/gallery/maps/popdens-2008.html.

Van den Bulte, C., S. Stremersch. 2004. Social contagion and income heterogeneity in new product diffusion: A meta-analytic test. *Marketing Sci.* **23** 530–544.

Wachter, R. 2006. Expected and unanticipated consequences of the quality and information technology revolutions. *J. Amer. Medical Assoc.* **295** 2780–2783.

Wang, J. C., C. L. Chen. 2004. An automated tool for managing interactions in virtual communities: Using social network analysis approach. *J. Organ. Comput. Electronic Commerce* **14** 1–26.

Wang, S. J., B. Middleton, L. A. Prosser, C. G. Bardon, C. D. Spurr, P. J. Carchidi, A. F. Kittler, R. C. Goldszer, D. G. Fairchild, A. J. Sussman, G. J. Kuperman, D. W. Bates. 2003. A cost-benefit analysis of electronic medical records in primary care. *Amer. J. Medicine* **114** 397–403.

Warshawsky, S. S., J. S. Pliskin, J. Urkin, N. Cohen, A. Sharon, M. Binztok, C. Z. Margolis. 1994. Physician use of a computerized medical record system during the patient encounter: A descriptive study. *Comput. Methods Programs Biomed.* **43** 269–273.

Wejnert, B. 2002. Integrating models of diffusion of innovations: A conceptual framework. *Annual Rev. Sociolgy* **28** 297–326.

Weston, F. 2001. ERP implementation and project management. *Production Inventory Management J.* **42** 75–80.

Zander, U., B. Kogut. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organ. Sci.* **6** 76–92.