Network Effects in Health Information Exchange Growth

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The importance of the Healthcare Information Exchange (HIE) in increasing healthcare quality and reducing risks and costs has led to greater interest in identifying factors that enhance adoption and meaningful use of HIE by healthcare providers. In this research we study the interlinked network effects between two different groups of physicians – primary care physicians and specialists – as significant factors in increasing the growth of each group in an exchange. An analytical model of interlinked and intragroup influences on adoption is developed using the Bass diffusion model as a basis. Adoption data on 1,060 different primary and secondary care physicians over 32 consecutive months was used to test the model. The results indicate not only the presence of interlinked effects, but also that their influence is stronger than that of the intragroup. Further, the influence of primary care physicians on specialists is stronger than that of specialists on primary care physicians. We also provide statistical evidence that the new model performs better than the conventional Bass model, and the assumptions of diffusion symmetry in the market are statistically valid. Together, the findings provide important guidelines on triggers that enhance the overall growth of HIE and potential marketing strategies for HIE services.

Categories and Subject Descriptors: K.6.0 [**Management of Computing and Information Systems**]: General—*Economics*; C.2.3 [**Computer-Communication Networks**]: Network Operations—*Network management*

General Terms: Economics, Management

Additional Key Words and Phrases: Health Information Exchange, diffusion of innovation, Bass model

ACM Reference Format:
Yaraghi, N., Du, A. Y., Sharman, R., Gopal, R. D., and Ramesh, R. 2013. Network effects in health information exchange growth. *ACM Trans. Manage. Inf. Syst.* 4, 1, Article 1 (April 2013), 26 pages.
DOI:http://dx.doi.org/10.1145/2445560.2445561

1. INTRODUCTION

The fraction of GDP devoted to healthcare in the United States is 17.6 percent [Congressional Budget Office 2010]. It is also the highest in the world and rapidly rising [Baicker and Skinner 2011]. In order to control the escalating medical costs while enhancing the quality of healthcare services, the U.S. Health Information Technology for Economic and Clinical Health Act (HITECH) requires all medical records to be in standardized digital forms by 2014 [Blumenthal and Tavenner 2010]. The principal objective of this act is to enable and require service providers to access

An earlier version of this paper was nominated for best paper award at WITS 2012.
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DOI:http://dx.doi.org/10.1145/2445560.2445561

medical data in a timely and cost-effective manner. The act also incorporates financial incentives to service providers for using digital data services as well as penalties for not doing so. This has created considerable pressure on both healthcare service units and individual practitioners to rapidly develop and adopt e-healthcare systems [Venkatesh et al. 2011].

Timely access to medical records can help physicians make better decisions, save more lives, and reduce huge costs by avoiding redundant tests or wrong diagnoses [Anderson et al. 2002; Bates et al. 1998, 1999; Brennan et al. 2005; Robinson et al. 2012]. A Health Information Exchange (HIE) is a Web-based service for sharing medical information among healthcare providers, and has been shown to be of significant importance in enhancing the quality, efficiency, and patient safety in healthcare systems [Bieszk et al. 2003; Fontaine et al. 2010a; Hincapie et al. 2010]. However, despite the potential benefits, the growth of HIEs has been limited and, in many cases, has fallen short of expectations [Agarwal et al. 2010b]. Financial factors [Fontaine et al. 2010b; Jha et al. 2009], functionality concerns [DesRoches et al. 2008; Poon et al. 2004], user resistance [Agarwal et al. 2010a; Reardon and Davidson 2007], privacy concerns [Anderson and Agarwal 2011; Angst and Agarwal 2009; Miller and Tucker 2009], and lack of strict governmental regulations [Bender et al. 2005; Ozdemir et al. 2011] are among the most studied barriers to the adoption of health information technology.

Many studies of e-healthcare systems have specifically focused on their adoption and usage by a variety of participating healthcare-providing entities. Based on a survey of a large number of physicians, Audet et al. [2004] conclude that adoption of IT tools is uneven, and that a technological divide exists between physicians, depending on their practice environment and mode of compensation. CW and E [2005] report that the most frequent use of IT tools by physicians is for billing purposes. By aggregating data in previous studies, Ford et al. [2006] provide some predictions for Electronic Health Record (EHR) systems in 2014. Ozdemir et al. [2011b] analytically investigate the adoption of EHR and the effect of electronic data sharing on consumer and provider surpluses. They report evidence that health-care providers may not have an incentive to share patients' records electronically. Miller and Tucker [2009] examine the effects of privacy protection laws in different states on the diffusion of electronic medical records. They find that state privacy protection of hospital medical information is significantly inhibiting EMR adoption.

Although the prior studies shed light on a number of drivers of and barriers to e-healthcare technology adoption, most of them are based on survey data focusing on practitioner perceptions in a single time period, and hence, do not directly address the temporal dimensions of adoption. The temporal dimensions include diffusion of awareness and participation at different levels in e-healthcare over time. Diffusion occurs through social contagion caused by endogenous and exogenous agents in the underlying healthcare communities and by the interactions between the drivers of and inhibitors to adoption. Moreover, the studies which are based on survey data rather than actual longitudinal observations of behaviors may introduce measurement errors which could limit the survey-based studies to outcomes that are only perceptible to community members [Angst and Agarwal 2009; Venkatesh et al. 2011]. In this study, we consider HIE as a multisided platform. HIE connects different sides of the healthcare market and facilitates the exchange of medical records among the different specialties of physicians. To operate efficiently, with all sides on board, is a crucial necessity for multisided platforms. We investigate the network externalities created between and among different sides of the healthcare market and study the relative role of these effects on attracting new members to the platform. The principal contributions of this research are threefold. We summarize them as follows.

First, we develop a novel HIE adoption model that extends the traditional Bass innovation adoption model [1969] to a group-based and interlinked network adoption process. This model views HIE as a multisided platform and characterizes the adoption process in terms of intra- and intergroup network externalities. We study two broad but distinct groups of HIE users, that is, primary care physicians and specialists, and the network externality effects on adoption among them. We refer to the cross-externalities between the two groups as the *interlinked network growth effects*. Similarly, we refer to the externalities arising out of imitating the innovators within each exclusive group as the *intragroup effects*. The social networks and multisided platform theories offer effective interpretations of these effects, as follows. The interlinked effects could result from the signaling across the weak ties between the two groups as well as the cross-externalities of increased values perceived, or even realized, by each respective group due to the growth in the other group over time. Similarly, the intragroup effects could result from cohesion, structural equivalence, and social contagion through word-of-mouth [Peres et al. 2010; Zhang et al. 2012].

Second, we conducted a longitudinal study of adoption behaviors over a three-year period to validate the proposed model and draw inferences. The data from this study provides the basis for a set of adoption-related analyses carried out as follows. Initially, we theoretically investigated the Bass diffusion model [Bass 1969] and the applicability of its assumptions in the HIE context. The Bass diffusion model considers a homogeneous adoption community, and hence does not account for the interlinked effects. Consequently, the assumptions of fixed innovation and imitation effects across the members of a single community will be violated in a heterogeneous population served by a multisided platform.

Third, we statistically show that the assumptions of diffusion curve symmetry and fixed innovation and intragroup imitation effects hold true in the proposed HIE adoption model. We also establish the explanatory power of the proposed model by showing that it is statistically preferred to the traditional Bass model. All the above contributions would also serve as substantial foundations for future investigations in this area, while also offering a theory grounded in the explanatory framework for the current study.

The article is organized as follows. Section 2 presents the related work in the field of network externalities. Next, Section 3 presents the theoretical and conceptual foundations of HIE market networks and introduces the longitudinal study conducted in this research. Section 4 develops the proposed network effects model, and Section 5 develops hypotheses on the effects proposed from this model. These hypotheses are derived from a theoretical analysis of adoption drivers and a patient-flow analysis of longitudinal usage logs by physician members of an HIE. Section 6 presents results on the statistical analyses on intragroup and interlinked effects, properties of the proposed adoption model and its statistical preference over the Bass model. In Section 7, we discuss the practical and theoretical implications of our findings. Finally, Section 8 presents the conclusions with directions for future research.

2. RELATED LITERATURE IN MULTISIDED PLATFORM ECONOMICS

Multisided market economics has attracted the attention of many researchers. The major difference between the multisided markets, as compared with the single-sided markets, is that the success of the multisided market depends on having all sides on board. A classic example of such markets is online dating Web sites. The platform connects men and women as two sides of the market. Since each member's perceived value depends on the number of members from the opposite sex on the other side, the platforms try to attract as many members as possible on both sides. The challenge in these markets is that all sides should be present to realize the optimal performance of the platform, but neither will have enough incentive to join without the other side already being on board. This problem is commonly referred as the "chicken and egg problem".

Evans [2003] points out three necessary conditions in order for a multisided platform to emerge: (1) existence of distinct groups of users; (2) creation of value for members of one side by the members on the other side; and (3) the possibility of facilitating coordination between members more efficiently than via direct bilateral relationships. He studies two cases of multisided platforms, palm OS and Diners Club payment cards, and points out three common business models among them. These include the importance of pricing strategies for both attracting and keeping all sides of the platform; the common occurrence of multihoming in these platforms; and starting as a small scalable platform as a solution to deal with the pricing complexity.

Parker and Van Alstyne [2005] show that network externalities will help a firm to invest in a product it intends to give away for free even in the absence of competition. The cost of giving free away products will be covered by the increased demand in the premium product as a result of the free product market. In this case, market complementarity arises from an internetwork externality. In the case of multisided platforms, this conclusion can be generalized by providing the service for free or at a reduced cost to the side that generates the maximum externality benefits.

Rochet and Tirole [2003] studied the competition and pricing models among the multisided markets and derived simple formulas governing the price structure in two-sided markets which also apply to a wide set of different governance structures, including private monopoly and a Ramsey planner. By briefly studying different cases of multisided platforms, such as credit cards, internet and video gaming consoles, they show that despite the differences among the pricing strategies of these platforms, their profits will be maximized when transactions between both sides of the market are maximized. This attracts more members on both sides, which is crucial to success.

Caillaud and Jullien [2003] analyze a model of imperfect price competition between multisided platforms. They show that these platforms have incentives to propose nonexclusive services to gain competitive advantage and larger market share. Based on this finding, they propose divide-and-conquer marketing strategies in which profits from one side of the market subsidizes the costs on the other side of the market.

The latter two studies on pricing strategies were developed in a greater extent by Armstrong [2006]. He studied three important models in pricing structure of multisided platforms: monopoly platforms, two-sided single homing, and competitive bottlenecks. The determinants of equilibrium prices are the magnitude of the cross group externalities, whether fees are levied on a lump sum or per-transaction basis, and whether agents join one platform or several platforms. As discussed in the previous section, most of the prior literature on e-healthcare technologies investigated diffusion from the end-users' point of view, which is a single-community perspective. To the contrary, HIE systems are multisided platforms that necessitate a multicommunity view of adoption.

HIE is a fairly new phenomenon and its multisided nature makes it very different from other e-healthcare systems. They face higher velocity of innovation and turbulence in revenues, market shares, and profits for firms [Baldwin and Clark 2000]. The direct and indirect network effects resulting from growing membership and participation in a multisided platform play very important roles in enhancing the values derived by the different constituting sides of the platform, and thus increasing future membership rates [Evans and Schmalensee 2007; Gawer 2009]. Furthermore, besides being multisided, the overall user environment of an HIE platform exhibits extensive interpersonal interactions among members of different user communities to which the HIE services are targeted. Potential members of the HIE system have a high degree of social interaction among themselves, and their decisions about joining a HIE services network are highly affected by social factors such as signaling, cohesion, and structural equivalence. These effects are also underscored by the fundamental motivations behind the multisided HIE systems. These platforms are designed to efficiently link and enhance communication and information-sharing among diverse providers in a healthcare services value chain.

In the current article we investigate the growth of HIE as a multisided platform, which facilitates the coordination between two distinct groups of users, that is, primary care physicians and specialists. The literature on HIE and the drivers of its growth as a multisided platform is still in its infancy, and this research is probably the first of its kind to consider HIE as a multisided platform and to study the effects of network externalities of different user groups on each other adoption behaviors. These externalities occur as intragroup growth within each group and as intergroup cross externalities among groups.

3. ANALYSIS OF HIE MARKET NETWORKS

We model the adoption processes in HIE market networks using the traditional Bass model [1969] as their theoretical foundation. In this section, we first summarize the basic concepts of the Bass model, its assumptions and limitations in the HIE market context. Next, we develop an analysis of HIE market structures and adoption processes. Subsequently, we describe the longitudinal study and the data sets used.

Innovation diffusion is the process by which an innovation spreads through certain channels over time [Mahajan et al. 1990]. The Bass model [1969] is a well-known diffusion model that depicts the successive increases in the number of adopters of an innovation over time. The potential adopters are either influenced by external sources (such as marketing and mass media) or internal sources (such as word-of-mouth). The first group is called the "innovators," while the second group is called the "imitators". The Bass model is derived from a hazard function and depicts the probability of adoption at time t, given that it has not yet occurred as

$$\frac{f(t)}{1-F(t)} = p + qF(t), \tag{1}$$

where $f(t)$ is the probability density of adoption at time t and $F(t)$ is the cumulative probability function. The coefficients of *innovation* and *imitation* are indicated by p and q, respectively. This nonlinear differential equation can be solved for $F(t)$ as

$$F(t) = \frac{1 - e^{-t(p+q)}}{\frac{q}{p}e^{-t(p+q)} + 1} \tag{2}$$

If we consider m as the total number of possible adopters in the market, then we can write Eq. (2) as

$$Y(t) = m\frac{1 - e^{-t(p+q)}}{\frac{q}{p}e^{-t(p+q)} + 1} \tag{3}$$

where $Y(t)$ is the cumulative number of adopters until time t. Jiang et al. [2006] prove that if $q > p$, then the Bass diffusion curve over the interval between 0 and $2T^*$ is symmetric with respect to $T = T^*$, where T^* is the time of peak adoptions. Using the Bass model as the viewing lens, we analyze the HIE market segments and their characteristics in the following discussion.

3.1. Market Segments and Interactions

The Bass model assumes a homogeneous population of adopters, where adoption takes place through word-of-mouth. The word-of-mouth propagation of ideas is assumed to occur randomly, and hence uniformly over the entire population. Although the Bass model could explain the diffusion of a variety of new products in different markets, it does not consider the facts that (a) a population could indeed be a network of individual entities or community members where the links between the network nodes would determine how communication is propagated; (b) the network could consist of different clusters or subnetworks with unique attributes; and (c) word-of-mouth communication could spread differently in each cluster [Valente 2010:20]. In the healthcare setting, although an HIE platform is a single exchange, it is marketed to physicians with very different characteristics. Due to their different specialties, a community of physicians would span significantly different market segments and members of the segments would have different networks of friends, colleagues, and professional associates. Therefore, diffusion of HIE services is not necessarily homogeneous as implied by the Bass model. In this context, the following observations on healthcare communities, with particular relevance to HIE market networks, are critical.

Physicians in general tend to form into broad subcommunities of *primary care* (internal medicine, pediatrics, family medicine, emergency medicine, and obstetrics/gynecology) and *specialists* (allergy and immunology, cardiology, pulmonary, infectious diseases, etc.). Typically, the first point of entry into a healthcare system for most patients is through the primary care physicians; patients access specialists mainly through referrals from the primary care physician.

A community of physicians in an HIE setting is not as large as the communities involved in traditional product markets. As a result, the interactions among physicians in an area tend to occur at three significant levels: *social/professional, patient-specific*, and *random.* The social/professional encounters may occur at professional meetings, hospital settings, and sponsored events, to name a few. The patient-specific interactions occur at two sublevels: *referral* and *non-referral*. The interactions through patient referrals occur among physicians when patients are formally referred by one physician to another. The nonreferral interactions occur when patients see physicians without formal referrals from other physicians who have seen them. A typical example of a nonreferral interaction occurs when a patient visits a hospital emergency room due to an acute situation, which later brings about an interaction between the emergency physician and the patient's family physician. In both referral and nonreferral based interactions, the patients and their medical records serve as the linkages between physicians. The significance of the social/professional and patient-specific interactions among the three modes of communication is an important departure from traditional product markets where the word-of-mouth effect is mostly a random phenomenon.

Members in each community tend to interact more with each other, both socially and professionally, rather than with members across communities. The referral-based interactions are *planned* between physicians and patients, and so are far greater between distinct groups of physicians than within a group. Contrarily, the nonreferral interactions are *unplanned*, and hence could be more sporadic. Note that the primary care physicians are the first points of contact for patients who are then referred back and forth between the primary care doctors and the specialists. So we may logically observe that a physician would encounter social/professional influences from within his group, a majority of patient-specific influences from outside his group through referral practices, and random influences from throughout the healthcare community. As a result, HIE adoption rates are not necessarily the same for different groups of physicians; the proclivity and disposition towards HIE adoption by specialists could be quite different from that of primary care physicians due to their different responsibilities, work situations, priorities, etc. Finally, the media may also influence people's adoption decisions differently [Valente 2010:177].

3.2. HIE Network Externalities

Despite their differences, the healthcare market segments have connections with each other not only due their professional contacts, affiliations, and associations, but also due to the increased value of the HIE to individual members, arising as a result of more members joining the network in each segment. Besides the value of data sharing, a new member who joins the system would also bring in more patient records to the database through their own consenting patients; consequently, this would increase the total amount of accessible data in the network, yielding increased values for the other members as well. Therefore, while the Bass model captures only the word-of-mouth effect in a uniform market population, we can easily observe that complex, utility-based network externality effects are in play in a multisegmented HIE market. Being a multisided platform, a HIE logically engenders both same-side and cross externalities among its constituent market segments. The same-side externalities can be regarded as intra-group effects and the cross externalities as the inter-linked group effects on HIE adoption.

We held extensive discussions with a team of medical experts, who indicated that primary care and specialist physicians comprise two distinct but related groups of HIE users. While it is possible to further classify these groups into specialty-based schemes, the experts agreed that the two broad groups would be sufficient for the scope of this study to adequately explain the interlinked effects between them. The experts also concurred that the interlinked effects are key drivers of adoption, and believed that these effects could typically be stronger than the intragroup effects. According to them, the patient-specific interactions, especially those occurring under referrals, could be significantly more effective in influencing adoption behaviors than the other modes of communication. Furthermore, most of the patient referrals occur between the primary care group and the specialist group; referrals within the specialist group, such as those from a specialist to a subspecialist are comparatively far fewer. Therefore, based on the experts' opinions and the above referral practices, we employed a classification strategy comprising of the two groups, primary care and specialists, in this research.

While intragroup adoption influences arise from the formal and informal networks that promote sharing domain knowledge and networking opportunities within a group, intergroup influences arise from typical patients treated by the two groups. Hence, the adoption of HIE by one group has the potential to enhance access to pertinent patient information and improve care given by the second group. Furthermore, we also expect that the two groups of primary care and specialist physicians affect each others' adoption behaviors, based on Granovetter's [1973] argument about the strength of weak ties in social networks. Members of each group tend to have more contact with each other than the members of the other group, and thus have the same access to the same information. Consequently, information received from colleagues within a group tends to be quite redundant. New information comes from weak ties, which are the ties to members of the other group. The weak ties enable the information to traverse bridges and connect otherwise disconnected groups [Valente 2010:182]. When more people join the system in one group, the probability of transferring the information to the other group increases, and thus the probability of adoption increases as well. In the current context, the weak ties are enabled through patient-specific interactions where the patients could serve as the signaling agents to both sides of the weak ties.

3.3. The Longitudinal Study

We studied HEALTHeLINK, which is a Web-based Regional Health Information Exchange Organization (RHIO) in Western New York. Created in 2008, it currently has over 2000 members consisting of physicians, nurse practitioners, nurses, and physician assistants. While most of these members are directly connected to HEALTHeLINK via their own interoperable EMR systems, they can also manually download data either through a Web portal called Virtual Health Records (VHR) or a Web service called ClinicalDocs, both operated by HEALTHeLINK. HEALTHeLINK provides three kinds of data: lab reports, radiology reports, and prescription data, all provided by major data providers consisting of hospitals, labs, and radiology units. HEALTHeLINK is a one-way highway of data flow from hospitals, labs, and radiology to users. Access to this data is subject to patient consent, which can be obtained at any participating healthcare-providing center. Once a patient consents, his/her medical data becomes available to HEALTHeLINK members.

HEALTHeLINK provides a central repository where the records of consenting patients are stored. Therefore, physicians do not directly exchange medical records with each other, but instead, simply download and upload data to the HEALTHeLINK servers. A principal source of the database is the Western New York hospital network system. When patients visit hospitals, their data records are originated upon consent and pushed to the HEALTHeLINK database. The data records grow in detail as further data is added by the labs, radiology centers, pharmacies, and service providers participating in the HIE. Patient consent is also requested when they visit individual physicians or group practices that participate in the HIE. Upon consent, these offices also serve as originators of HEALTHeLINK data records. Therefore, as more physicians join the HIE, the chances are greater that patients will consent upon recommendations of their physicians, and thus their medical records become available on the HIE system.

We analyzed two different HEALTHeLINK data sets in this research: an adoption data set and a usage data set. The usage data set was employed to derive plausible hypotheses on the intragroup and interlinked network effects of the proposed model. The adoption data set was used to test these hypotheses. The adoption data set consists of the member name, specialty, affiliation, and adoption date of all the current members of the HIE system since the date on which the first member joined the system for 32 consecutive months. Since members join HEALTHeLINK at the practice level rather than the individual level, we excluded large practices (with over 80 members) to ensure that the decision about joining the system was made individually and thoughtfully. For the same reason, we have excluded nurses, physician assistants, and nurse practitioners from our study. These professionals work under the supervision of a physician and typically belong to a practice, and thus do not make independent decisions about joining the system. They become members of HEALTHeLINK automatically when their practice or supervising physician joins the HIE. After these refinements, we identified a total of 1061 physician members of HEALTHeLINK. Of these, 680 were primary-care physicians and 381 were specialist physicians. Figure 1 shows the adoption trend on each group over the period in which data was collected.

According to Figure 1, the specialists and primary care physicians closely follow similar patterns in the number of adoptions each month. The increase or decrease in the number of adoptions in a group seems to closely mirror the corresponding changes in the other group. Intuitively, this seems to indicate that the innovation and intragroup imitation effects in the two groups are nearly the same. Furthermore, if we do not consider certain months such as July 2010 that recorded abnormal peaks in the number of adoptions, a gradual increasing trend in the number of adoptions over time can be

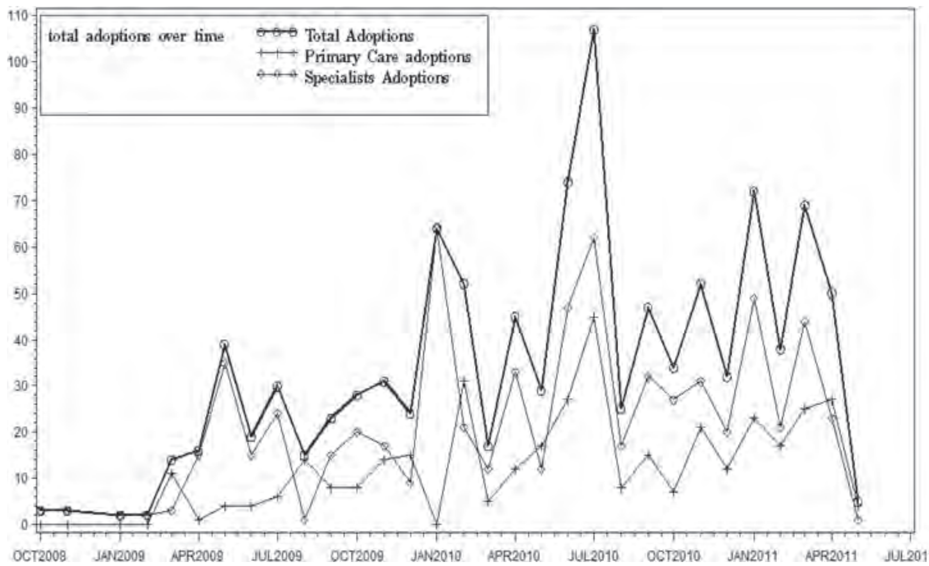

Fig. 1. Adoption trends in different groups.

observed. The adoption behaviors that may be intuitively observed from Figure 1 are formally specified and tested within the framework of the proposed network-effects model.

The usage data set that we analyzed was extracted from the access logs of the HEALTHeLINK Web system, which shows the users who have viewed a specific type of a patient's medical records. This data set has been identity-proofed by thorough cleaning and protected from revealing the identities of patients or HIE members. The identity-proofing involved assigning random identity numbers to patients and the HIE members and enabling access to their records only through these random numbers. The identity-proofed data set shows the accesses to each patient's record by HIE members over time. After cleaning the data, we obtained 35,063 such accesses to patient records from 2009 to 2011. Note that a patient record could be accessed by multiple physicians and that a physician could access multiple patient records. This data was further cleaned and processed to yield 11,701 unique patient records that we accessed via the HIE members during this period. The access patterns that were identified from this data set were used to determine the patient flows among the different physician groups. The patient flows were then used to formulate hypotheses on the parameters of the proposed network-effects model and were subsequently tested. These hypotheses are grounded in social networks and multisided platform theories.

4. THE NETWORK EFFECTS MODEL

The multiple modes of interaction among physicians in a heterogeneous HIE market in fact represent multiple channels of communication and influence over adoption decisions. Therefore, unlike the traditional Bass model, which assumes a uniform but time-dependent word-of-mouth diffusion rate over an entire homogeneous market, the diffusion rates in a heterogeneous and segmented market like HIE will vary across different segments. Hence, the proposed model incorporates a different imitation coefficient for each group, denoted as q_1 and q_2, respectively. Similarly, the model includes two different innovation coefficients for the respective groups, denoted as p_1 and p_2.

This is because the effect of the communication channels on HIE adoption is not necessarily the same among primary care and specialist physicians.

Besides the imitation effects within each group separately, there could also be such imitation effects between groups. This is because a group of potential adopters are not only affected by the previous number of adopters within the same group (intragroup effect), but also simultaneously by the total number of adopters in the other group as well (interlinked effect). For example, when a new member in the primary care group joins the HIE, it could increase the word-of-mouth not only among the other primary care physicians but also in the specialist group, and vice versa. However, the intragroup and interlinked effects are different, since a new member probably has stronger ties within his/her group, and thus the intragroup effect has a different impact on him/her than the interlinked effect. In this context, the intragroup effects can be seen as the outcomes of social/professional and random influences and the interlinked effects as the outcomes of patient-specific and random influences. Similar to the imitation effects in a group being amplified by the total number of adopters within the same group until time t, the imitation effect of adoptions in the first group due to the adoptions in the second group is amplified by the total number of adoptions in the second group.

Let the probability density of adoption in group i at time t be $f_i(t)$. We extend the traditional Bass model to simultaneous adoptions in two separate but interlinked groups, as follows.

$$f_1(t) = [p_1 + q_1 F_1(t) + q_{21} F_2(t)]\,[1 - F_1(t)] \tag{4}$$

$$f_2(t) = [p_2 + q_2 F_2(t) + q_{12} F_1(t)]\,[1 - F_2(t)] \tag{5}$$

In Eqs. (4) and 5, p_i and q_i are the respective innovation and imitation coefficients for group i, and q_{ij} is the imitation effect of group i on group j. The nonlinear differential Eqs. (4) and (5) are transformed into the set of simultaneous Eqs. (6) and (7) which estimate $Y_i(t)$, *for* $i = 1, 2$, the cumulative number of adopters in group i at time t as a function of time and the cumulative number of adopters in the other group. The derivations of Eqs. (6) and (7) are given in the Appendix.

$$Y_1(t) = m_1 \frac{1 - e^{-(q_1+p_1)t + \frac{q_{21}}{m_2} Y_2(t)\left(\frac{1}{q_1+p_1} \ln \frac{q_1}{p_1} - t\right)} - \frac{q_{21}}{p_1 m_2} Y_2(t) e^{-(q_1+p_1)t + \frac{q_{21}}{m_2} Y_2(t)\left(\frac{1}{q_1+p_1} \ln \frac{q_1}{p_1} - t\right)}}{\frac{q_1}{p_1} e^{-(q_1+p_1)t + \frac{q_{21}}{m_2} Y_2(t)\left(\frac{1}{q_1+p_1} \ln \frac{q_1}{p_1} - t\right)} + 1} \tag{6}$$

$$Y_2(t) = m_2 \frac{1 - e^{-(p_2+q_2)t + \frac{q_{12}}{m_1} Y_1(t)\left(\frac{1}{p_2+q_2} \ln \frac{q_2}{p_2} - t\right)} - \frac{q_{12}}{p_2 m_1} Y_1(t) e^{-(p_2+q_2)t + \frac{q_{12}}{m_1} Y_1\left(\frac{1}{p_2+q_2} \ln \frac{q_2}{p_2} - t\right)}}{\frac{q_2}{p_2} e^{-(p_2+q_2)t + \frac{q_{12}}{m_1} m_1 Y_1(t)\left(\frac{1}{p_2+q_2} \ln \frac{q_2}{p_2} - t\right)} + 1} \tag{7}$$

Note that the simultaneous system of Eqs. (6) and (7) extends the traditional single-dimensional Bass model to two dimensions represented by the two groups. The parameters of the model can be estimated from simultaneous equation-modeling using adoption data on each of the groups over time. Once the parameters are estimated, the solution of the simultaneous system of equations over a continuous time interval would yield the diffusion curve for each of the two groups. As can be seen from the structure of the two equations, the two curves are related over time, and hence can be numerically estimated over any time interval. In fact, such an extension to n dimensions when n groups are involved is fairly straightforward, albeit algebraically tedious. In the following discussion, we present an analysis of the usage logs that led to the formulation of formal hypotheses on the parameters of the network effects model.

4.1. Stages, Drivers, and Effects

In this section we will briefly present the Rogers [2003] theory of diffusion. We will reflect on each stage of this model with regard to the HIE adoption in healthcare market. The hypotheses in Section 4 are built in part upon the discussion in this section.

Rogers models the innovation-decision process in terms of five different stages: *Knowledge, Persuasion, Decision, Implementation,* and *Confirmation*. In the knowledge stage, an individual is first exposed to the existence of an innovation. In the Persuasion stage, an individual forms a favorable or unfavorable attitude toward the innovation. Next, an individual engages in activities that lead to a choice to adopt or reject the innovation in the Decision stage. Implementation occurs post-adoption, beginning with the usage of the innovation. Finally, the Confirmation stage is reached is when an individual either seeks reinforcement of an innovation decision already made or reverses a previous decision to adopt or not [Rogers 2003]. In this analysis, we focus only on adoption; the study of actual usage or implementation of the HIE system is beyond our current scope. Hence, we consider only the first three stages of innovation-decision process in the following analysis.

Rogers also identifies two channels of communication: mass media and interpersonal communications. Mass media and marketing efforts are effective in creating awareness among the consumers about an innovation, and hence play important roles in the Knowledge stage. Interpersonal communications are the most important channels of information-sharing and mutual influence among peers in the Persuasion and Decision stages. Based on these notions, we posit that the mass media and marketing campaigns are the driving forces behind the creation of awareness and knowledge about the HIE system. Since the innovators are the first to react to such campaigns, we also posit that the innovation effects will be predominant during the Knowledge stage.

Next, Rogers argues that in the Persuasion stage, an individual may mentally apply the new idea to his/her situation before deciding on whether or not to try it. In the HIE context, this implies three principal drivers of adoption in the Persuasion stage, as follows. First, physicians may evaluate the possible benefits of the HIE for their practices. If the HIE system offers higher potential value to their practice needs, then the likelihood of favorable attitudes emerging towards the HIE system would also be higher. We term this driver the *perceived value of the HIE*. Second, physicians could look for competitive advantage from the HIE system in many communities where physicians compete for typically insurance-supported patients. Drawing from social networks theory, we call this driver the *structural equivalence* among physicians in a group. Third, when patient referrals occur across groups, the adoption or nonadoption of one physician could persuasively influence the other physician in a referral relationship. Furthermore, besides being carriers of information, the individual patients involved in a referral could also influence the physicians involved in their adoption decisions. For example, when a physician referring a patient to another is a member of the HIE and the patient consents to the online record, it is perceivable that the physician to whom the patient is referred is quite likely to be influenced by three elements: the referring physician, the patient, and the online record. If the referred physician is not already a member, then the three elements together could be influential in the persuasion process. Similarly, the influences could work in the opposite direction as well. Again drawing from social networks theory, we term this driver as *signaling over weak ties* between the two groups. In this context, we posit that the specialists who receive most of the referred patients from primary care physicians could see a higher potential value from the HIE system, and thus tend to be more favorable towards adoption as a result than vice versa. While all the above three drivers would lead to interlinked network effects, the structural equivalence would also drive intragroup imitation effects.

Table I. Effects, Drivers and Predominant Stages

Stage	Effect Driver	Effect Type
Knowledge	Marketing Campaigns Mass Media	Innovation Effects
Persuasion	Perceived Value of HIE Signals over Weak Ties Structural Equivalence	Interlinked Network Effects Intra-Group Imitation Effects
Decision	Cohesion Random Interactions	Intra-Group Imitation Effects Interlinked Network Effects

In the Decision stage, Rogers points out that ways to reduce the uncertainties surrounding the consequences of adopting an innovation are either to try out the new idea on a partial or limited basis, or to rely on the experiences of trials with the innovation by peers. From the viewpoint of social networks theory, this implies *cohesion*. Cohesion in the HIE context takes place when physicians actively seek information from their peers about their beliefs and usage experiences with the system. The patients in both referral and nonreferral instances also contribute to this knowledge. As the patient flow among the physicians increase, we posit that the effects of cohesion could become predominant at the Decision stage. A principal consequence of cohesion is the imitation effect. Imitation could occur either as an intragroup effect or as an interlinked effect.

Competition and learning define structural equivalence and cohesion as their respective drivers of social contagion in adoption [Burt 1987]. Although it is not possible to clearly distinguish the effects of these two processes from each other, we argue that the structural equivalence plays a more important role among primary care physicians due to the higher degree of competition among them. This can be seen intuitively, as follows. First, the primary care physicians typically outnumber specialists in any community. Second, the proportion of community-wide patients seen by primary care physicians far outnumbers those seen by the specialists. However, the revenue per patient to a specialist would be much higher than that for a primary care physician. Consequently, primary care physicians earn by patient volume while specialists by revenue margin. The higher volume of patients clearly indicates that a HIE system could offer greater value to primary care physicians than specialists. Hence the competitive advantages due to HIE adoption could be greater for primary care physicians than specialists, leading to the hypothesis that structural equivalence is a stronger driver of adoption in primary care than in specialist care. Cohesion, on the other hand, plays a more important role among specialists. The competition among specialists may not be as strong as that among the primary care physicians due to their smaller numbers, more specialized skills, and higher revenue margins. However, they learn about the HIE system through common patients and professional colleagues, leading to a more cohesive adoption practice. Table I summarizes the discussion above in terms of effect types, their drivers, and the stages where they would predominantly occur.

4.2. Patient Flow Analysis

The network effects intuitively developed as above can be hypothesized in terms of the values of the network effects model parameters and their interrelationships. In order to formally derive these hypotheses, we carried out a patient flow analysis with the HIE usage data. The identity-proofed usage data set was first restricted to a set of data records with four fields: patient ID, physician ID, physician type, date of visit. We analyzed a random sample of this data set to identify the visitation traces for patients over the two-year period 2009-11. This sample contains 11,701 unique patient visits to 333 primary care physicians and 194 specialists. When a patient visits a physician

Table II. Categorization of Patient Visits in the Sample

Transition type	Description	Effect	Number of transitions
Primary care to Primary care – Type 1	Patient visits primary care first and then revisits a primary care	Drives structural equivalence	708
Primary care to specialist – Type 2	Patient visits primary care and then visits a specialist	Increases value for specialists	914
Specialist to primary care – Type 3	Patient returns to a primary care after visiting a specialist	Increases value for primary care physicians	824
Specialist to specialist – Type 4	Patient is referred to a second specialist from the first specialist	Drives Cohesion	359
Primary care only – Type 5	Patient visits primary care and never visits a physician again	No effect	7106
Specialist only – Type 6	Patient visits specialist and never visits a physician again	No effect	1790

multiple times in a row without visiting any other physician in between, only the first visit is considered in the analysis, since there has not been any information transmitted between physicians via these visits. Since a patient could visit multiple physicians and each physician could have multiple patients visiting, the set of patient visits falls into six categories of transitions between and within two groups, as shown in Table II.

The patients that visit a physician can be categorized into three distinct groups: without any referral; with a referral from a physician of the same group; and with a referral from a physician of the other group. Type 1 transitions in Table II could be either referral or nonreferral patients. Transition types 2-4 are from patients under referral categories, and types 5-6 are nonreferral. Since, we have 333 primary care and 194 specialists in the sample, the visitation data is averaged per physician of each group, as follows. First, note that 7,106 patients visited primary care physicians once, but never again (Type 5). This averages to (7106/333) = 21.33 nonreferral patients visiting a primary care physician. Similarly on average (1790/194) = 9.22 nonreferral patients visit a specialist once but never again (Type 6). Now, consider type 1 transitions. Whether by referral or nonreferral, these patients visit more than one primary care physician. This type averages to 2.12 such patients per primary care physician. Similarly, the types 2-4 average to 4.71, 2.47, and 1.85 patients per physician of their respective groups. Furthermore, on average, a primary care physician receives 25.93 patients while a specialist receives 15.78 patients. These computations and their respective percentages of patients in each group are summarized in Table III.

The patient flow analysis sheds considerable light on the patient-specific influences on HIE adoption and supports the analysis of the drivers and effects discussed earlier. The following contingency table shown in Table IV is obtained using the average data on transition types 1-4 from the patient flow analysis results in Table III. The contingency table uses the categorical variable of patient visits, which could be either to a primary care physician or a specialist. The hypotheses on adoption effects are derived from Table IV. These are developed in the following section.

5. HYPOTHESES

The hypotheses on the parameters of the network effects model are classified into innovation, intragroup imitation, and interlinked network effects. These hypotheses are developed from the theoretical and empirical foundations presented in Section 3.

5.1. Innovation Effects

Based on the attributes of HIE markets discussed in Section 2, we argue that the innovation coefficients for potential adopters will not be different. Although the HIE

Table III. Patient Flow Analysis

Physician	Patient Visit Type	Percentage
Primary care	Only a primary care physician (Type 5)	82.26%
	A pr. care phy. followed by another pr. care phy. (Type 1)	8.19%
	A specialist followed by a primary care physician (Type 3)	9.53%
Specialist	Only a specialist (Type 6)	58.43%
	A primary care physician followed by a specialist (Type 2)	29.84%
	A specialist followed by another specialist (Type 4)	11.72%

Table IV. Contingency Table of Patient Visits

	Primary care	Specialists
Primary care	8.19%	29.84%
Specialist	9.53%	11.72%

market is segmented into primary care physicians and specialists, the main channels of communication and marketing efforts are the same in both the segments. Furthermore, our discussions on the management of HEALTHeLINK revealed that no separate marketing or media strategies were adopted for the two segments, and both were exposed to the same marketing campaigns. Moreover, the Federal incentives for meaningful use of HIE systems do not distinguish between primary care physicians and specialists. All of these arguments lead to a hypothesis that primary care and specialist physicians would react similarly to a newly introduced innovative HIE service. This is specified in the following hypothesis, which states that coefficients of innovation for primary care and specialist physicians will be equal.

H1: Same HIE marketing efforts will have the same outcomes on innovation in primary care physicians and specialists; Thus $p_1 = p_2$.

5.2. Intragroup Imitation Effects

We observe that structural equivalence could play a more important role in the intragroup effects of the primary care group than in the specialist group; similarly, cohesion could be a stronger influence in the specialist group than in the primary care group for these effects. While these two behaviors represent different causal factors, the end results are the same in both the groups, that is, adoption by imitation. Based on these observations and our discussions with the marketing group at HEALTHeLINK, we hypothesize that the net intragroup effects between the two groups can be comparable. We draw additional evidence from the patient flow analysis to support this position. Referring back to Table IV, we observe that the percentage of patients that follow a primary care to primary care physician sequence is a 8.19%; similarly, the percentage that follows a specialist to specialist sequence is 11.72%. In terms of absolute values, these percentages are equivalent to 2.12 and 1.85 patients per primary care physician and specialist, respectively. The comparability of these figures indicates that the circulation of information and influence arising out of patient-specific interactions within the two respective groups are nearly the same. This is consistent with the earlier position observed using the drivers of intragroup imitation effects. This is specified in the following hypothesis which states that coefficients of intragroup imitation for primary care and specialist physicians will be equal.

H2: Imitation will have similar outcomes in primary care physicians and specialists; Thus $q_1 = q_2$.

5.3. Interlinked Network Effects

Although the primary care and specialist physicians are modeled as distinct HIE market segments, they are also interdependent, primarily through their referrals-based patient-centric interactions. However, the consequential effects of these drivers on each of the segments could be different. The growth in HIE membership in each segment is not only affected by the intragroup influences of each segment, but also by the growth in the other segment. Several works on marketing research literature have modeled multimarket diffusion with cross-country influences [Ganesh et al. 1997; Kumar and Krishnan 2002; Van Everdingen et al. 2005]. Cross-country effects are a result of two influence sources: weak ties and signals [Peres et al. 2010]. Both weak ties and signaling mechanisms were shown to be effective and significant in prior marketing literature [Putsis Jr. et al. 1997; Sarvary et al. 2000]. Further, potential consumers in a market are affected by diffusion of the innovation in other markets. Successful diffusion in a market will reduce the perception of risk and increase the legitimacy of using the new product in other markets [Peres et al. 2010]. Based on these studies and other arguments given in the earlier section, we hypothesize that the interlinked network effects are crucial to successful adoption of HIE services, and these effects are driven by a combination of factors such as perceived value of HIE, signaling over weak ties, structural equivalence, and cohesion. We draw additional evidence from the patient flow analysis to support this position, as follows.

Referring back to Table IV, we observe that the percentage of patients that visit a specialist after a referral from a primary care physician is 29.84%; similarly, the percentage that returns to the primary care physician after a visit to a specialist is 9.53%. In terms of absolute values, these percentages are equivalent to 4.71 and 2.47 patients per specialist and primary care physician, respectively. This flow reveals that the HIE system would create significant value to each market segment due to the significant referral and return patterns. If a particular primary care physician adopts the system, he/she will be able to access the medical records of his/her patients in 9.53% of the time. Similarly, the potential benefit of HIE system for a specialists will be the possibility of accessing 29.84% of the patients medical records. These observations are consistent with the theoretical and literature-based reasons for the interlinked effects described above. Accordingly, we derive the following hypotheses on interlinked effects.

H3-1: Increase in adoption of HIE system by primary care physicians will positively affect the adoption by specialists; Thus $q_{12} > 0$.

H3-2: Increase in adoption of HIE system by specialists will positively affect the by primary care physicians; Thus $q_{21} > 0$.

We further argue that besides the value of data sharing, a new member who joins the system would also bring in more patient records to the database via their own consenting patients. Consequently, this would increase the total amount of accessible data in the network, yielding increased value for the other members as well. The increased utilities represent the *cross-externalities* between the primary care and the specialist sides of the HIE platform. We propose that the specialists tend to derive more value from a HIE when more primary care physicians join than vice versa. The reasons for this assertion are twofold. First, the community of primary care physicians is much larger than that of the specialists. Second, being the first point of contact, the primary care physicians have access to a much larger set of patients than the specialists, In fact, as noted earlier, the patient population seen by the specialists can be considered a subset of the much larger patient population seen by the primary care physicians. Therefore, when a primary care physician joins the HIE, he/she would bring a larger set of patient records to the HIE than when a specialist joins, and consequently be of more value to the specialists than vice versa. This effect is also confirmed by patient flow analysis results. As discussed before, according to Table IV, a primary care physician will be able to view the medical records of 9.53% of his/her patients (which are created by specialists), while this ratio is 29.84% for specialists. The potential benefits of HIE in terms of ratio of available patient records is significantly higher for specialists as compared with primary care physicians. Thus we hypothesize that not only the interlinked effect exists between the two groups, but also that the interlinked effect of primary care physicians on specialists is more powerful than the interlinked effect of specialists on primary care physicians. This hypothesis is stated as follows.

H3-3: The effect of adoption by primary care physicians on specialists is stronger than the effect of adoption by specialists on primary care physicians; Thus $q_{12} > q_{21}$.

Following the logic in the previous part, we observe that the percentage of patients that a primary care physician receives from other primary care physicians is 8.19%, while the percentages of patients that have previously visited a specialist is 9.53% percent. The higher percentages of patients received from specialist groups in addition to their potential impact as change agents—due to their higher degree of specialization in the medical profession—lead us to hypothesize that the interlinked network effects of specialists on primary care physicians is higher than the intragroup imitation effect for primary care physicians.

H3-4: The effect of adoption by specialists on primary care physicians is stronger than the imitation effect of adoption by other primary care physicians; Thus $q_{21} > q_1$.

Similarly, from Table IV we observe that the percentage of patients that a specialist receives from other specialists is 11.72%, while the percentage of patients that a specialist receives from primary care physicians is 29.84%. The large difference between these two percentages reflects a much stronger interlinked network effect of primary care physicians on specialists than the intra-group imitation effects within a specialists group.

H3-5: The effect of adoption by primary care physicians on specialists is stronger than the imitation effect of adoption by other specialists; Thus $q_{12} > q_2$.

6. EMPIRICAL RESULTS

We present three sets of results in this section. First, we present the results on the test for symmetry of the diffusion curve. Second, we present the estimation results of the interlinked network effects model. Third, we carry out an econometric evaluation of the conventional Bass model estimates of adoption in each group in comparison with those derived from the interlinked network effects model.

6.1. Diffusion Curve Symmetry

As discussed in Section 2, the Bass model assumes that the diffusion curve is symmetric. In other words, it assumes that the number of adoptions peak in the middle of the overall adoption period. To check the validity of this assumption in our data set, we used the symmetry test provided by Randles et al. [1980].[1] In this test, the null hypothesis is that the distribution is symmetric, so if the p-value of the test is not small enough to reject the null hypothesis, we can conclude that the symmetry is not rejected, and hence the sample distribution is not skewed. Since the Randles test

[1] In the Randle's test, all possible triples (x_i, x_j, x_k) of observations of a series of $X_1, X_2, ..., X_T$ are considered. For a series with T observations, (n ¦ k) combinations of such triples can be identified. A triple is a right (left) triple when the middle observation is closer to the smaller (larger) observation than to the larger (smaller) observation. In a symmetric distribution, there are as many right as there are left triples. If there are relatively more right triples, the underlying distribution is skewed to the right. The asymptotic distribution of the test statistic is standard normal, so we can use conventional critical values for hypothesis testing.

Table V. Symmetry Test Results

Parameter	Estimate
Sample skewness	0.5782
L-Skewness I	0.1429
L-Skewness II	1.333
Symmetry test statistic	1.445
P value	0.1479

is not very common, there is no built-in procedure available in SAS or any other statistical analysis package to perform this test. However, Mandrekar et al. [2007] have developed an SAS macro for performing this test; we used their macro to test for the symmetry of the diffusion curve.

In addition to the Randles test results, we present sample skewness and two extra measures of skewness developed by Hosking [1990] in Table V.

According to the results shown in Table V, although the sample is slightly left-skewed, the null hypothesis that the population is symmetric cannot be rejected, and thus we can justify the application of both the traditional Bass model and the interlinked network effects model on the HIE adoption data.

6.2. Analysis of Network Effects

The sets of Eqs. (6) and (7) are estimated jointly using the nonlinear three-stage least squares option of MODEL procedure [SAS Institute Inc 2008, 675–690]. The ordinary least squares (OLS) estimation method is not appropriate because the estimators of the structural coefficients are biased and inconsistent due to the simultaneity bias. Instead, the methods of two-stage least squares (2SLS) or three-stage least squares (3SLS) should be used. Three-stage least squares method was suggested by Zellner and Theil [1962] to estimate simultaneous equation systems. It is a combination of two-stage least squares and seemingly unrelated regression methods and uses the two-stage least squares estimated moment matrix of the structural disturbances to estimate all coefficients of the entire system simultaneously. The major difference between 2SLS and 3SLS lies in the assumptions underlying the random errors in the simultaneous equations. If the random errors are correlated, then 3SLS is more appropriate than 2SLS because it produces more efficient estimates. Such correlations among the random errors could be present if other possible contingency variables are unintentionally omitted from the simultaneous contingency model, leaving the influence of these omitted variables to be absorbed by the random errors of the equations, and consequently, rendering the correlated random errors [Lin and Shao 2000]. Nonlinear least squares has been shown to produce more efficient estimates in the context of the Bass diffusion model [Srinivasan and Mason 1986].

Based on the population of physicians in the community served by HEALTHeLINK, the initial estimations of the Bass diffusion model in a single market and discussions with the administrators of HEALTHeLINK, the values of m_1 and m_2 were set at 866 and 457, respectively. This was done in order to reduce the number of parameters to be estimated in the equation systems of Eqs. (6) and (7) such that the ratio of available observations and model parameters is large enough for the model to converge. Table VI shows the parameters estimates for $p_1, p_2, q_1, q_2, q_{12}$, and q_{21}. All of them are highly statistically significant.

The results reveal that the interlinked network effects q_{12} and q_{21} are greater than the within-group effects ($q_{21} > q_1$ and $q_{12} > q_2$). This finding shows a very interesting relationship between groups, where the members of a group are more affected by members of the other group rather their own group members. Moreover, the effects of

Table VI. Parameter Estimations for Simultaneous Eqs. (6) and (7)

Parameter	Estimate	Approx Std. Err.	t Value	Approx $p_r > \|t\|$
p_1	0.006915	0.00136	5.09	<0.0001
q_1	0.001888	0.000582	3.23	0.0032
p_2	0.00872	0.00205	4.25	0.0002
q_2	0.003579	0.00121	2.95	0.0065
q_{21}	0.015158	0.00387	3.91	0.0003
q_{12}	0.03048	0.00742	4.10	0.0006

Table VII. Hypotheses Test Results[2]

Hypothesis	Statistic	$P_r > \chi^2$
H_1	0.69	0.4054
H_2	1.95	0.1629
H_{3-1}	15.30	<0.0001
H_{3-2}	16.85	<0.0001
H_{3-3}	4.19	0.0407
H_{3-4}	16.22	<0.0001
H_{3-5}	18.70	<0.0001

adoption by primary care physicians on specialists are higher than the effects of specialists' adoption on primary care physicians ($q_{12} > q_{21}$). Both these results can be explained by the higher value that each member receives from a person in the other group joining the exchange. Note that a specialist would benefit more when a primary-care physician joins the system compared with the benefits of another specialist joining the exchange.

Table VII shows the results of the tests of hypotheses, $H_1, H_2, H_{3-1}, \ldots, H_{3-5}$. All seven hypotheses are well supported at the $p < 0.05$ level. In summary, this implies: (a) both primary care physicians and specialists react similarly to commonly targeted marketing and media campaigns; (b) both behave similarly in imitating the innovators in their respective groups; (c) both show significant mutual influences on adoption with the primary care physicians influencing the specialists more than vice versa; and (d) interlinked network effects are stronger than the intra-group imitation effects in both the groups.

6.3. Performance of the Interlinked Network Effects Model

We estimated the innovation and imitation coefficients by using the conventional Bass model as shown in Eq. (3) for each of the market segments. The results are shown in Table VIII. Note that since there are only three parameters in each model to be estimated, the model easily converges without fixing m_1 or m_2. Thus we also estimated the values of m_1 and m_2 in this analysis. These estimates have been used as the fixed parameter values in prior estimation methods discussed earlier.

It is interesting to note that when the interlinked effects do not appear in the model, the imitation effects are estimated to be considerably higher. We have also tested the hypotheses H_1 and H_2 based on the estimation results of conventional Bass model.

When the interlinked network effects are not taken into account, the coefficients of innovation (p_1 and p_2) and the coefficients of imitation (q_1 and q_2) are not equal

[2]For H_1 and H_2 the null hypothesis is equality of parameters, thus large p-values, which support the research hypothesis.

Table VIII. Parameter Estimates of Conventional Bass Model for Two Groups of Physicians

Parameter	Estimate	Approx Std. Err.	t Value	Approx $P_r > \|t\|$
p_1	0.00553	0.000320	17.28	<0.0001
q_1	0.145326	0.00854	17.02	<0.0001
m_1	866.30	36.8568	23.50	<0.0001
p_2	0.003294	0.000315	10.46	<0.0001
q_2	0.17512	0.0108	16.18	<0.0001
m_2	457.2267	20.6535	22.14	<0.0001

Table IX. Hypotheses Test Results Based on Estimates from Table VIII

Hypothesis	Statistic	$P_r > \chi^2$
H_1	24.78	<0.0001
P_2	4.67	0.0307

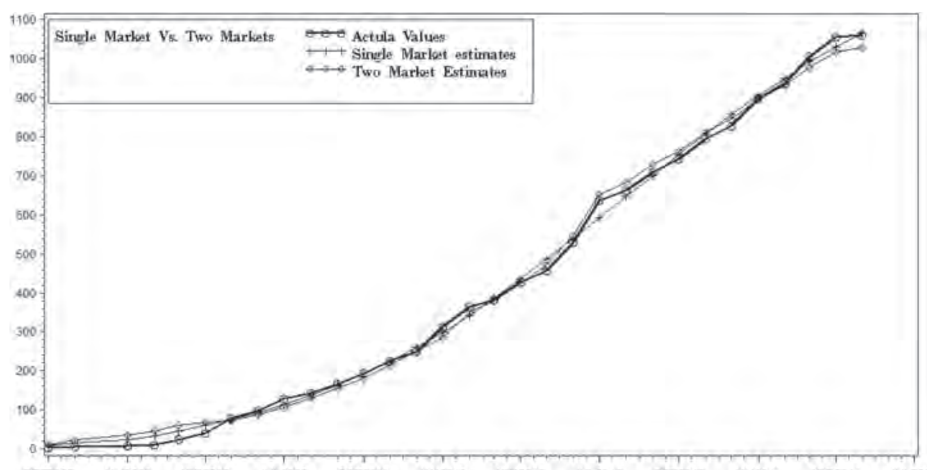

Fig. 2. Comparison of actual adoption data with estimates of adoption by the two models.

respectively in two market segments. This result also shows that the interlinked effects are dominant forces in the two-group HIE market. At a more intuitive level, this result also reveals the following: when taken into account in combination with the other effects, the interlinked network effects would provide a more accurate description of the adoption behavior; and when not taken into account in such a manner, the significant impact of the interlinked network effects could be unevenly distributed among the other forces of adoption.

The above interpretations can also be seen from the comparative adoption charts shown in Figure 2. This figure shows a comparison of the estimates of adoption derived from the traditional single-market Bass model with the proposed two-market interlinked network effects model. This figure also shows the actual number of adoptions in the 32 months of data we had collected. As can be seen from this figure, the two-market interlinked effects model more closely captures the actual adoption behavior than the single-market Bass model. This intuitive observation is statistically validated using the econometric analysis described below.

The usual methods for testing the goodness-of-fit between actual observations and their estimates such as an F-test cannot be applied to compare the non-nested models, since we are required not merely to select variables but simultaneously to find an appropriate functional form. A series of econometric studies since the early 1960s have investigated different statistical tests for choosing among competing models. The first work in this area was by Cox [1962]. Cox's test is a generalization of the likelihood ratio test, which investigates the validity of the null hypothesis of how a set of data was generated by comparing the log of the likelihood ratio between H_0 and H_1, with an estimate of the expected value of this quantity if H_0 were indeed true. Pesaran [1974] showed how this idea could be applied to non-nested linear regression models. Pesaran and Deaton [1978] extended Pesaran's technique to deal with nonlinear and multivariate regression models. It allows us to test whether the truth of one model can be maintained, given the performance on the same data of an alternate model. The roles of the two models can of course be reversed, and it is entirely possible that both, or neither, may be rejected. Davidson and MacKinnon [1981] proposed two new tests for the univariate nonlinear regression case. These tests, which are known as the J-test and the P-test, have the same purpose and essentially the same properties as the Cox, Pesaran and Deaton tests, but are conceptually simpler, and are very easy to implement using existing computer software, and thus have attracted the attention of researchers, including IS researchers (e.g., [Hu et al. 1997; Loh and Venkatraman 1992]). For a complete review of the tests, see MacKinnon [1983].

Davidson and MacKinnon [1982] provided a version of tests for comparing multivariate models such as simultaneous equation systems. Since the models that we have used are also systems of simultaneous equations, newer versions of the P-test and J-test were applied for comparing them with each other as discussed in Davidson and MacKinnon [1982]. We briefly discuss this in the following.

Consider f and g as reduced forms of two competing models of simultaneous equation systems. We can construct the null and alternative hypotheses as

H_0: $y_{it} = f_{it}(X_t, \beta) + \varepsilon_{it}$

H_1: $y_{it} = g_{it}(Z_t, \gamma) + \varepsilon_{it}$

Where $i(= 1, (m))$ is the index of the equation and $t(= 1, ..., n)$ is the index of the observation.

By nesting H_0 and H_1 in an artificial compound model, we have

$$y - \widehat{f} = \alpha\ (\widehat{g} - \widehat{f}) + \widehat{F}b + \varepsilon \tag{8}$$

Where $y, \widehat{f}, \widehat{g}$, and ε denote vectors of length mn formed by stacking y_{it}'s, f_{it}'s, g_{it}'s and ε_{it}'s, respectively. $\widehat{F}$ is a $mn \times k$ matrix formed by stacking the derivatives of f_{it} with respect to β evaluated at $\beta = \widehat{\beta}$. b is a k vector of the coefficients and α is a single coefficient to be estimated. Under H_0, the vector ε is distributed as $N(0, \Omega_0 \otimes I_n$ and thus (8) shall be estimated by generalized least squares (GLS) using an assumed covariance matrix proportional to $\widehat{\Omega_0}$.[3] The test statistic is simply the ordinary t-statistic for a test of $\alpha = 0$. If α is statistically indifferent from zero, then H_0 is the true model. However, the rejection of H_0 does not necessarily imply the truth of H_1. To test whether H_1 is the true model, it has to be used as H_0 and tested against the other alternative as H_1 [Davidson and MacKinnon 1982].

We followed the work of Hu et al. [1997] and Loh and Venkatraman [1992] before comparing the Bass model with the proposed interlinked effects model, and tested both models against the white noise model to check if the diffusion model is completely random or not. The white noise model is a random process defined as

$$N(t) = N(t-1) + \varepsilon(t) \tag{9}$$

[3]For derivation of reduced forms of Eqs. (6) and (7) contact the first author.

Table X. Model Comparisons with White Noise: t-values with Probabilities

Null model	Alternative model	
	Bass	Interlinked
White noise	4.73 (<0.0001)	5.24 (<0.0001)

Table XI. Bass Model and Interlinked Effects Model Comparisons: t-Values with Probabilities

Null model	Alternative model	
	Bass	Interlinked
Bass	N/A	16.99 (<0.0001)
Interlinked	0.75 (0.4576)	N/A

in which the $N(t)$ is the number of adopters as time t, and $N(t-1)$ is the total number of adaptors at time $t-1$ and $\varepsilon(t)$ is a random error with normal distribution $N(0, \sigma_{\varepsilon}^{2})$.

Given the estimated values of two models, we consider the white noise model as the null hypothesis and test its truth against the Bass model and the proposed interlinked effects model. Note that if H_0 is a linear regression model—which is the case for white noise model in (45)—then the estimates of the J-test and P-test will be identical, since in this case, $\widehat{F_i} = X_i$ and $\widehat{f_i} = X\widehat{\beta}$ is simply a linear combination of the repressors [Davidson and MacKinnon 1982, 782]. Based on the test results shown in Table X, the null hypothesis that the diffusion of HIE among physicians is random is rejected by both models.

As discussed above, in order to compare the conventional Bass model with the proposed model, we performed the P-test by the reduced forms of (6) and (7). The partial derivatives were calculated numerically according to the derivative formula $\frac{f(x+h)-f(x)}{h}$ when $h \to 0$ upon recommendation of Davidson and MacKinnon [1982, 555].[4] As shown in Table XI, the Bass model is rejected in favor of proposed interlinked network effects model, while the proposed model is not rejected in favor of the Bass model.

7. DISCUSSION

Our empirical analyses revealed strong cross-externalities between the sides of the HIE platform, confirming this observation. Next, we studied the data on HIE usage by the two groups of physicians over a two-year period. This study revealed the following insights on the HIE market: (i) the innovation and intragroup imitation effects are more or less the same in both the physician groups; (ii) strong interlinked effects on both sides exist; (iii) interlinked effects could be stronger than intragroup effects in influencing adoption decisions in both the groups. Interestingly, observation (i) indicates that the two physician groups do not differ in terms of cohesion, structural equivalence, and social contagion, while observations (ii) and (iii) indicate that signaling across weak ties and the cross-externalities could be stronger forces than cohesion, structural equivalence, and social contagion in the two-sided HIE market. We considered the patient flows between the groups as the signaling agents over the weak ties. Accordingly, this observation also reveals that patients could be powerful carriers of information and influencer of adoption across groups of physicians. Motivated by these observations, we carried out detailed econometric analyses on the longitudinal

[4]For analytical derivation of partial derivatives contact the first author.

data set, which led to the following conclusions. The longitudinal analyses statistically confirmed observations (i), (ii), and (iii) and also showed that the interlinked effect of primary care physicians on specialist is more powerful than that of specialists on primary care physicians. This important finding has strong strategic implications and provides a basis for designing effective HIE marketing strategies to enhance adoption and create sustainable business models for such platforms.

We have investigated the direct and indirect network effects among and between two groups of HIE users, primary care physicians, and specialists. We have shown that the intralinked network effects among both primary care physicians and specialists are weaker than the interlinked network effects between them. Moreover, the interlinked effect of primary care physicians is the strongest among all. This finding is of crucial importance in designing both marketing strategies and pricing models for the HIE platforms. Pricing models in multisided networks are designed to attract the most possible members to both sides by subsidizing the membership fees for the most influential side. The findings of this research about the great externality effect of primary care physicians can be used in the venue of designing pricing models to attract more members to the system. Since the governmental supports of the HIE systems will gradually lessen in the near future, platforms have to design stable business models for their survival. The findings of this research will not only be of interest to designing pricing models, but also in creating different marketing campaigns for attracting the greatest number of potential members.

We have also compared the performance of our model against the conventional Bass model, and have statistically shown that our version of that model is a better tool for predicting the market fluctuation and understanding the underlying derivers of adoption in the HIE market. This model is fairly general and can be easily applied in other contexts of multisided markets, such as online dating websites and credit card platforms. We are currently working on an extended version of this model, which can be used in estimating the market growth in platforms that connect more than two sides.

8. CONCLUSION

We have developed a comprehensive model to predict diffusion of HIE, based not only on imitation and innovation factors within the market, but also based on external sources of influence form other segments of the market. These sources of influence are driven by weak ties, signaling, and increased value of the system accrued due to HIE participation of others, structural equivalence and cohesion factors. This model could also be used to predict diffusion of other similar innovations and market types. We have demonstrated the network effects through a detailed longitudinal study of adoptions in an HIE. We have also statistically established the validity of the model, symmetry in the diffusion data, and the statistical preference over the traditional Bass adoption model.

Our analysis reveals that the word-of-mouth effect and the increased value proposition are present not only within groups in the healthcare market but also have a strong impact on HIE adoption between groups. We have further analyzed a usage date set to determine the patient flow between and within the two groups. Results from this analysis explain the previous findings and confirms the validity of our conclusions about the interlinked effects on adoption.

The findings of this research can be used to develop marketing strategies for promoting adoption of HIE systems among different groups of healthcare providers. Considering the findings about the higher impact of primary care physicians on specialists, we may conclude that the marketing recourses are to be focused on attracting more primary care physicians. A limitation of this study could be the relatively short period time for adoptions (32 months) since the innovation was introduced. However, the idea of HIE itself is fairly new in the US market and it is most likely to take several years before the technology matures. In this context, this research initiates a productive line of research on HIE adoption, and will serve as the foundations for further research as our experience with such systems grow over time. Some of the important areas of future research that emerge from this work are the inclusion of the impact of targeted marketing on HIE adoption, study of usage levels and their interactions with the adoption of health exchanges, and research on the impacts of the economic policies of the federal and state governments on the adoption of healthcare exchanges. On a more conceptual level, studies on the different underlying social networks and their interactions would shed considerable light on the social behaviors guiding the adoption of HIE systems. We are currently pursuing some of these avenues.

APPENDIX

This appendix presents the derivation of Eqs. (6) and (7) from Eqs. (4) and (5). We derive Eq. (7) from Eq. (5). Eq. (6) is driven from Eq. (4) in a similar way.

Consider Eq. (5): $f_2(t) = [p_2 + q_2F_2(t) + q_{12}F_1(t)]\,[1 - F_2(t)]$.

Since $\mathrm{f(t)} = \frac{\mathrm{dF(t)}}{\mathrm{dt}}$ we can write Eq. (5) as

$$\frac{dF_2(t)}{dt} = [p_2 + q_2F_2(t) + q_{12}F_1(t)]\,[1 - F_2(t)] \tag{8}$$

(by substituting $f_2(t)$ by $\frac{dF_2(t)}{dt}$ in Eq. (5)). And thus

$$\frac{1}{[p_2 + q_2F_2(t) + q_{12}F_1(t)]\,[1 - F_2(t)]}dF_2(t) = dt. \tag{9}$$

Integration of both sides of Eq. (9) results in

$$\int \frac{1}{[p_2 + q_2F_2(t) + q_{12}F_1(t)]\,[1 - F_2(t)]}dF_2(t) = t + D, \tag{10}$$

Which can be simplified as

$$F_2(t) = \frac{q_2 - p_2e^{-(t+D)(q_2+p_2+q_{12}F_1(t))} - q_{12}F_1(t)e^{-(t+D)(q_2+p_2+q_{12}F_1(t))}}{q_2(1 + e^{-(t+D)(q_2+p_2+q_{12}F_1(t))})}. \tag{11}$$

In addition we must have

$$F_2(0) = 0 \text{ and} \tag{12a}$$

$$F_1(0) = 0, \tag{12b}$$

that is, nobody adopts the HIE system before it starts. Solving the equation system consisting of Eqs. (11), (12a), and (12b), we obtain the value of D as

$$D = -\frac{1}{q_2 + p_2}1\mathrm{n}\frac{q_2}{p_2}. \tag{13}$$

Substituting Eq. (13) back into Eq. (11), we have

$$F_2(t) = \frac{1 - e^{-(p_2+q_2)t+q_{12}F_1(t)(\frac{1}{q_2+p_2}1\mathrm{n}\frac{q_2}{p_2}-t)} - \frac{q_{12}}{p_2}F_1(t)e^{-(p_2+q_2)t+q_{12}F_1(t)(\frac{1}{q_2+p_2}1\mathrm{n}\frac{q_2}{p_2}-t)}}{\frac{q_2}{p_2}e^{-(p_2+q_2)t+q_{12}F_1(t)(\frac{1}{q_2+p_2}1\mathrm{n}\frac{q_2}{p_2}-t)} + 1}. \tag{14}$$

Finally, since $Y_1(t) = m_1 F_1(t)$ and $Y_2(t) = m_2 F_2(t)$, we can derive Eq. (14) as

$$Y_2(t) = m_2 \frac{1 - e^{-(p_2+q_2)t + \frac{q_{12}}{m_1} Y_1(t)(\frac{1}{p_2+q_2} 1\text{n} \frac{q_2}{p_2} - t)} - \frac{q_{12}}{p_2 m_1} Y_1(t) e^{-(p_2+q_2)t + \frac{q_{12}}{m_1} Y_1(\frac{1}{p_2+q_2} 1\text{n} \frac{q_2}{p_2} - t)}}{\frac{q_2}{p_2} e^{-(p_2+q_2)t + \frac{q_{12}}{m_1} m_1 Y_1(t)(\frac{1}{p_2+q_2} 1\text{n} \frac{q_2}{p_2} - t)} + 1}.$$

Following the same steps, Eq. (6) is similarly derived from Eq. (4).

ACKNOWLEDGMENTS

For their valuable comments, the authors are grateful to Russell Davidson, Hashem Pesaran, and the seminar participants in the 21st Workshop on Information Technologies and Systems (WITS).

The results presented in this article rely on the data collected at HEALTHeLINK. We thank Dan Porreca and John Grieser for their support.

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Received April 2012; revised September 2012; accepted January 2013