Professional and geographical network effects on healthcare information exchange growth: does proximity really matter?

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ABSTRACT

Background and objective We postulate that professional proximity due to common patients and geographical proximity among practice locations are significant factors influencing the adoption of health information exchange (HIE) services by healthcare providers. The objective of this study is to investigate the direct and indirect network effects of these drivers on HIE diffusion.

Design Multi-dimensional scaling and clustering are first used to create different clusters of physicians based on their professional and geographical proximities. Extending the Bass diffusion model to capture direct and indirect network effects among groups, the growth of HIE among these clusters is modeled and studied. The network effects among the clusters are investigated using adoption data over a 3-year period for an HIE based in Western New York.

Measurement HIE adoption parameters—external sources of influence as well as direct and indirect network coefficients—are estimated by the extended version of the Bass diffusion model.

Results Direct network effects caused by common patients among physicians are much more influential on HIE adoption as compared with previously investigated social contagion and external factors. Professional proximity due to common patients does influence adoption decisions; geographical proximity is also influential, but its effect is more on rural than urban physicians.

Conclusions Flow of patients among different groups of physicians is a powerful factor in HIE adoption. Rather than merely following the market trend, physicians appear to be influenced by other physicians with whom they interact with and have common patients.

INTRODUCTION

Health information exchanges (HIEs) are web-based services for efficiently sharing medical information among healthcare providers and have been shown to be of significant importance in enhancing the quality of healthcare.[1–3] Prior research shows that HIEs increase efficiency and safety of healthcare systems.[4–7] Regional health information organizations (RHIOs) enjoy substantial governmental support.[8–10] Despite all these, the growth of HIEs has been limited and in many cases has fallen short of expectations.[11 12] Existing research sheds considerable light on some of the important barriers to HIE adoption. Poor project management due to lack of comprehensive understanding of product specifications and lack of adequate standards for interoperability among electronic medical record (EMR) systems are the main technical factors that have impeded the adoption of HIEs. Healthcare providers on the other hand, have been concerned with high initial costs and lack of perceived benefits, limited technical support, patient privacy risks, and legal issues.[13–15] Existing literature investigates e-healthcare technology adoption mostly from individual end users' perspectives. However, HIEs present entirely new value propositions; they are *multisided platforms* that bring together two or more distinct but interdependent and interacting members. Such platforms are of value to any member only if the other members are also present and engage in interactions. Multisided platforms grow in value to the extent that they attract more users over time to join and participate in a networked community, a phenomenon known as the *network effects*. The value of each member to other members depends on the relationships between them. These relationships can be represented by grouping members into different market segments or groups. In such a market, the network effects are either direct (within group) or indirect (between groups). Direct (within group) effects are driven from the value that members receive from the members of the same group. Indirect (between groups) effects are driven by the benefits that members of a group receive from the participation of members in each of the other groups. In other words, within and between groups network effects are driven by the value offered by the members of each group to members of the same and other groups, respectively.[16–19] In this paper, we will use the terms 'within group effect' to refer to direct network effects and 'between group effects' to refer to indirect network effects.

Since healthcare professionals have both social and professional interactions outside of the patient care context, sociological factors such as cohesion, structural equivalence, weak ties, and signals could significantly influence HIE adoption. These concepts are outlined in table 1 and their effect on HIE adoption is portrayed in figure 1.

The multisided value propositions of HIE discussed above imply that the value that the HIE brings to the healthcare providers could also be a critical driver in HIE adoption decisions. Since the purpose of HIE is to facilitate access to clinical information about shared patients, the value of HIE for each provider depends not only on the number of other providers who have adopted HIE but also on the extent to which he or she shares

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Table 1 Glossary of technical terms used in this paper

Definition of sociological factors	
Cohesion	The tendency of the members of a group to unite and make similar decisions. Cohesion focuses on socialization between members in a social network. The more frequent and empathic the communication is between members, the more likely that a member's adoption will trigger others. For example, 'when a new drug appears, doctors who are in close interaction with their colleagues will similarly interpret for one another the new stimulus that has presented itself, and will arrive at some shared way of looking at it'.[21 22]
Structural equivalence	The tendency of the members to compete for keeping a high status in the social network. Structural equivalence highlights competition between members in a social network and generally applies to the competition of people merely using one another to evaluate their relative adequacy. For example, 'two physicians trying to keep up with the rush of medical developments in order to live up to their image of a good physician and maintain their position in the social structure of medical advice and discussion.'[22]
Weak ties	The links that connect two different cliques or subgroups together in a social network. Weak ties can convey the ideas between the two market segments much more efficiently than those who have strong ties only within a single market segment.[23]
Signals	The implicit indication of innovation characteristics that a market segment receives from the adoption of the similar innovation in another market segment. Successful diffusion of an innovation in a market segment will create positive signals so that it reduces the perception of risk and increases the legitimacy of using the new product in the other segment.[24]
Definition of technical terms in Bass model	
Bass model for innovation diffusion	Explains the adoption process as a function of external and internal sources of influence.
External sources of influence	The sources which affect adoption from outside a market segment, such as mass media advertisements and government support.
Innovators	The early adopters of an innovation. According to the Bass model they adopt an innovation under the influence of external sources.
Innovation coefficient	In the Bass model, it captures the effects of external sources of influence.
Internal sources of influence	The sources which affect adoption from inside a market segment, such as word of mouth, cohesion, and structural equivalence.
Imitators	The late adopters of an innovation. According to the Bass model they adopt an innovation under the influence of internal sources.
Imitation coefficient	In the Bass model, it captures the effects of internal sources of influence.
Definition of technical terms in our model	
Multisided platform	A system that connects or facilitates the connection, transaction, or communication between different groups (sides) of users.
Network effects (network externality)	The effects of a user on the potential value of a multisided platform for other users.
Direct network effects (within group effects)	The *value* that a user creates for the other users on the same side of the multisided platform.
Indirect network effects (between group effects)	The *value* that a user creates for the other users on the other sides of the multisided platform.

patients with those other providers. This suggests that in order to model HIE adoption, providers should be grouped based on shared patients, so that direct (within group) and indirect (between group) network effects can be examined. In our previous work, we were able to demonstrate that an HIE adoption model that takes network effects into account performs much better than classical models in which the network effects are ignored.[20] In this paper we present two alternative grouping methods. One is based on actual data from an HIE reflecting shared patients between 864 providers over a 3-year period. The second uses geographical location, based on the assumption that patients are more likely to visit physicians that are in close vicinity to one another. In both instances, based on the value created by shared patients, we expect to find high within group effects and low between group effects. By HIE adoption, a practice provides an option for its affiliated physicians to start using HIE services. The physicians, individually, make their own decision as to whether or not adopt HIE. The benefits of HIE will only be realized when adoption happens at individual physician rather than practice level. In this paper, we focus on physicians and use the term 'adoption' to refer to the event when a physician downloads a medical document from HIE for the first time. As a robustness check, we also analyze the adoption at practice level and provide the results in part 3 of the online supplement.

Investigating the effects of shared patients among physicians on HIE growth, along with other factors such as marketing efforts and the influence of different market segments on each other, provides a means of comprehensive quantitative evaluation of the effects of shared patients. Highlighting the relative importance and powerful effects of patient flow in comparison with other drivers of adoption such as governmental supports, will provide insights for HIE platforms to make strategic decisions for promoting their services and growing their network of members.

RESEARCH BACKGROUND

To be consistent with the current body of knowledge in the context of health information technology, in this paper we use the exact terminology defined by National Alliance for Health Information Technology (NAHIT).[25] These definitions are summarized in table 2.

Innovation diffusion is the process by which an innovation spreads through certain channels over time.[26] Diffusion of innovation theory was introduced by Rogers[27] and then further developed by Bass[28] to consider two major sources of influence: *internal*, such as word-of-mouth and influences by peers; and *external*, such as mass media advertisements. The Bass model was further developed by marketing researchers to accommodate other market characteristics such as geographical locations,[29] dynamic number of potential adopters,[30] multi-innovation,[31] and multi-stage markets.[32]

The Bass[28] model depicts the successive increase in the number of adopters of an innovation over time. The potential adopters are influenced by either external sources such as mass media or internal sources such as word-of-mouth, cohesion, and structural equivalence. Some individuals decide to adopt an innovation independently of the decisions of other individuals

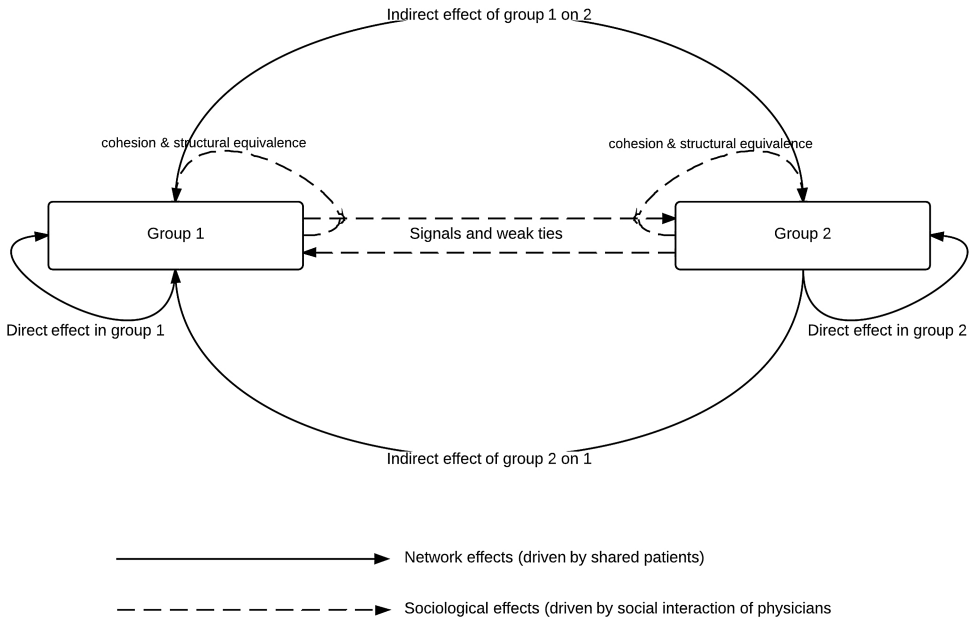

Figure 1 Graphical representation of network effects in multisided platforms.

in a social system. Bass refers to them as 'innovators'. Other individuals are influenced by the pressure of social systems which increases over time with the number of previous adopters. These individuals are 'emulators' (in marketing literature, including the original work by Bass, this group of adopters is usually referred as 'imitators'). The Bass model explains the total number of adoptions in each time period as a function of the total number of people who have already adopted the new innovation and the total market size. There are three main parameters of interest in the Bass model: market size, innovation coefficient, and emulation coefficient.

The Bass model considers a single and homogenous market in which the emulation and innovation have equal effects on every potential adopter. This may not necessarily hold true in the HIE market. Although an HIE system is a unique product, it generates a multisided market where the distinct segments interact in HIE usage. Consequently, the growth of HIE in each segment is affected by its own strength and those of the other segments. The between group effects of different market segments on each other to adopt new products have been widely studied in the marketing literature.[24 33–35] As shown in table 1, *weak ties* and *signal*s are two mechanisms that are shown to cause the indirect (between groups) effects in different market segments.[36 37] In addition to these well studied factors that drive between group effects, in the context of HIE, the value of the system for each member also affects adoption. Since the purpose of HIE is to facilitate access to clinical information about shared patients, the value of HIE for each provider depends on not only the number of other providers who have adopted HIE but also the extent to which he or she shares patients with those other providers. This unique feature of HIE distinguishes it from the other common innovations that have been previously studied and warrants the investigation of the within group network effect resulting from the value created by the flow of shared patients, as a significant driver of HIE diffusion.

Therefore, while the Bass model captures the internal and external sources of effects in one homogeneous segment, a complex, value-based network effect is in play in the current context. To bridge these gaps, considering a network with k different groups, we model the adoption as a function of external sources (such as mass media), direct (within group) network effects, and indirect (between groups) network effects. This model will enable us to investigate the effects of the potential value of HIE for each group of physicians and test different hypotheses with regard to the effects of shared patient flow among healthcare providers. The online supplement provides the mathematical derivation of the model.

Table 2 Definition of HIE, HIO, and RHIO

Term	Definition
Health information exchange (HIE)	The electronic movement of health-related information among organizations according to nationally recognized standards.
Health information organization (HIO)	An organization that oversees and governs the exchange of health-related information among organizations according to nationally recognized standards.
Regional health information organization (RHIO)	A health information organization that brings together healthcare stakeholders within a defined geographical area and governs health information exchange among them for the purpose of improving health and care in that community.

MULTISIDED PLATFORM GROUPS

A set of users should possess a high degree of homogeneity in attitudes and behaviors in order to be considered as a group. Attention has also focused on consumption as a means of expressing self-identity and group membership, and of reinforcing and strengthening group cohesion and unity.[38–40] Moreover, communication or interaction and the sharing of a common language are often important boundary lines staking out differences and similarities in consumption.[40 41] As suggested by the literature, we use *common behavior*, *self-identity*, and *common communication channels* as the basis for grouping potential HIE members.

Grouping by common patients: professional proximity

In accordance with previous discussions on the role of communication channels and common language in grouping consumers, in an electronic prescription records (EPR) adoption study, Davidson[41] characterizes communication genre by substance and form and argues that physicians and nurses have different genres of communications based on their different roles and tasks. We argue that patients who visit different specialties can also be considered as a medium of communication between physicians. These patients have health issues that require specific types of specialties to interact with each other during their care. Thus those specialties that have the highest patient overlap tend to have a specific genre of medical communication with each other and can be considered as a group. This clustering strategy is based on the concept of a group in the multisided platforms context. This is also driven from the common-interest based clustering widely used in marketing.[40] Medical specialties that have a high overlap of common patients tend to need the prior medical data recorded by each other more than those created by physicians with whom they do not share patients. This common need creates a common interest for the specific set of physicians within each group. Applying the methodology proposed by Yaraghi *et al*,[42] we used HIE system log files of 230 000 medical records of 14 870 patients sent to 864 different physicians, and applied multi-dimensional scaling and clustering methods to create different clusters of medical specialties. The members in each cluster have the highest possible level of common patients among themselves and the lowest possible level of common patients with the members of other clusters (see online supplement for details).

Grouping by common location: geographic proximity

Hägerstrand[43] viewed diffusion as a transformation of a population with a low rate of adopters to a population with a higher rate of adopters by means of information diffused through both external and internal channels of communications. In their recent work, Onyile *et al*[44] have shown the importance of considering geographical location of patients in success of HIE platforms. Other examples of classification of consumers based on their geographical location include recent works that have investigated the innovation diffusion among consumers in different countries and their interlinked impacts on each other.[33 35] Following the path of prior research, we grouped HIE members based on their geographical location proximity and studied their effect on one another.

HYPOTHESES

Innovations acquire the momentum to spread in a network as the number of adopters increases. When an HIE acquires a new member, it increases the probability of adoption by other potential members through well studied mechanisms of *cohesion* or *structural equivalence*.[22] In addition, different groups also affect each other's adoption through *signals* and *weak ties*.[23 24] The famous study of Coleman *et al*[21] reveals that structurally equivalent doctors tend to adopt innovations in tandem.[45] These effects are intensified or attenuated by the hierarchical levels of groups; for example, physicians tend to have a stronger impact on nurses since they are at the top of the clinical hierarchy.[46 47] These factors have been shown to affect the diffusion of innovations; however, in the context of multisided platforms, the potential value that users can acquire by membership of other users with whom they interact the most can have significant effects on their adoption behavior.

As depicted in figure 1, the adoption in one group can affect the other group's adoption through signals, weak ties, and shared patients. The number of shared patients is the driver of the HIE value. When we group physicians so that the flow of shared patients between groups is minimized, we are eliminating the patient flow from the between group effects and thus expect the between group effects to be only driven by signals and weak ties. On the other hand, since the number of shared patients is maximized within each group, the value of HIE for members in each specialty group increases as another physician within the same group adopts the system.

Considering the groupings based on common patients, we hypothesize that adoption by physicians is more likely to be affected by the adoption of those with whom they share a large number of patients. This is driven not only through cohesion and structural equivalence, but also through the increased value that HIE system brings to members with a high degree of dependency on shared medical records.

- *H1-1*: The effect of adoption by physicians in a specialty group on other physicians in the same specialty group is positive and statistically significant.
- *H1-2*: The effect of adoption by physicians in a specialty group on other physicians in the same specialty group (within group effect) is stronger than on physicians in the other specialty groups (between groups effect).

The impact of geographical location on diffusion of HIE systems is even more important due to the multisided nature of the platform. Since the ultimate goal of the system is to provide access to medical records for the users, its proposed value may be different for members based on their location and other means of accessing data that they can substitute for the HIE system. A related argument is that new technology adoption can be affected by the relative inconvenience of using existing channel alternatives.[48] The cost of using other alternatives (ie, accessing paper medical records) for physicians located in rural areas is higher than for those located in urban areas (due to the longer distance to hospitals and other data providers). Similar studies on information systems diffusion have confirmed the importance of cost of access to alternative substitutes on adoption behavior.[49 50] This will render the value of an HIE system higher for them as compared with those in urban areas. Moreover, physicians located in rural areas often receive data from the data providers that are located in urban areas since most medical facilities such as labs, pharmacies, and radiology centers are located in urban areas. Thus, we hypothesize that the between group effects from members located in urban areas are stronger than from those located in rural areas. This is in accordance with the existing literature which states that diffusion is expected to proceed from urban centers to remote locations.[43 51]

- *H2-1*: The effect of adoption by physicians in urban areas on physicians in rural areas is stronger than the effect of adoption by physicians in rural areas on physicians in urban areas.

Since most marketing efforts are focused in urban rather than rural areas, we expect that in rural areas the effect of word-of-mouth (as represented by internal effects) will be greater than the effect of marketing. We expect the opposite in urban areas.

- *H2-2*: In rural areas, the effect of adoption by other physicians in both rural and urban areas is stronger than the marketing effect.
- *H2-3*: In urban areas, the marketing effect is stronger than the effect of adoption by other physicians in both rural and urban areas.

DATA AND METHODS

We studied HEALTHeLINK, a web-based RHIO in western New York. Created in 2008, HEALTHeLINK currently has over

2000 members of different medical specialties. While most of these members are directly connected to HEALTHeLINK via their own interoperable EMR systems, they can also manually download data through either a web portal called Virtual Health Records (VHR) or a web service called ClinicalDocs, both operated by HEALTHeLINK. HEALTHeLINK provides three kinds of services: *lab reports*, *radiology reports*, and *hospital transcriptions data*, all provided by major data providers consisting of hospitals, labs, and radiology units. HEALTHeLINK acts as a highway of data flow from hospitals, labs, and radiology units to healthcare providers. 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. The future members of HEALTHeLINK will not be able to access the medical records of the patients who have consented prior to their membership date.

We analyzed three different datasets in this research: *adoption*, *usage*, and *location*. The adoption dataset is publicly available on the HEALTHeLINK website and includes the name, specialty, affiliation, and adoption date of all the current members of HIE system for 35 consecutive months, starting when the first member joined the system. The usage dataset consists of all medical records that are uploaded by any of the data providers (labs, radiology centers, or hospitals) on the HEALTHeLINK system. This dataset identifies each medical record with a unique patient ID and the ordering physician ID. Based on this we could identify the total patients that each type of specialty has had as well as the common patients between each pair of specialties. Finally, the location dataset is derived as follows. The members of HEALTHeLINK are affiliated with over 360 practices; we used Google Maps to get the latitude and longitude of each of these practices and then used the two dimensions for clustering analysis. Each member is assigned to each of the two geographical clusters based on the location of the practice they are affiliated with. Multidimensional scaling and ward clustering methods have been used to form the professional and geographical proximity clusters. The network effects have been analyzed using the non-linear three-stage least squares method. Details of these analyses are given in the online supplement.

RESULTS

We present below the estimation results on the two effects studied in this research.

Professional proximity network effects

The specialties have been grouped into three clusters according to their professional proximities. As described in the online supplement, the members in each of these groups have the highest ratio of common members among themselves. Accordingly, the extended Bass model considers the interaction of these three clusters in which the adoption rate in each group is estimated as a function of within group and between group effects of adoption by the same group and other groups, respectively, and the independent effects of marketing on each group. This requires the estimation of 12 parameters as shown in table 3. We could also estimate the potential market size in each cluster (m_1, m_2, and m_3) in equation set (2) in the online supplement. However, since our dataset is limited to 3 years as HEALTHeLINK is relatively new, this could cause overestimation and convergence problems. Therefore, we fixed the market size parameters based on the recommendations of HEALTHeLINK analysts.

As shown in table 3, all of the within group effects (q_{ii}) are statistically significant, while the between group effects, except the effect of group 1 on 3 (q_{13}), are not significant; thus hypothesis H1-1 is fully supported while H1-2 is partially supported. It is very interesting to note that the within group effect (q_{ii}) in all groups of specialties is much more powerful that the innovation effect (p_i). As discussed before, the coefficient of emulation captures the time varying factors affecting adoption, including social contagion obtained from structural equivalence and cohesion. In previous adoption models, the emulation (imitation) coefficient was assumed to be equal in every market segment and thus was not able to capture the increased values of the multisided HIE platform for one side as the membership in other sides increases. In this model, we could distinguish between emulation from members of a physician's own group of specialties (q_{ii}) and the emulation from members in other specialty groups (q_{ij}, where $i \neq j$). We show that the emulation coefficient is not equal for every member of the social system and is highly affected by the value perceived by a member on joining the system. This shows that adoption of HIE is a very informed decision, derived from careful examination of possible outcomes it may have for physicians rather than mere social contagion and following other members in the network. Physicians are much more influenced by those that they have the highest level of common patients with than those with little

Table 3 Estimation results for specialty based groups

Parameter	Description	Estimate	SE	t Value	$P_r > \|t\|$
q_{11}	Emulation effect within group 1	0.1201	0.0397	3.02	0.0050
q_{22}	Emulation effect within group 2	0.0938	0.0291	3.23	0.0030
q_{33}	Emulation effect within group 3	0.1400	0.0596	2.35	0.0254
p_1	Innovation effect in group 1	0.0138	0.0072	1.91	0.0655
p_2	Innovation effect in group 2	0.0190	0.0058	3.23	0.0027
p_3	Innovation effect in group 3	0.0186	0.0105	1.77	0.0864
q_{12}	Emulation effect from group 1 on group 2	0.0409	0.0201	1.95	0.0602
q_{13}	Emulation effect from group 1 on group 3	0.3716	0.1262	2.94	0.0061
q_{21}	Emulation effect from group 2 on group 1	−0.0304	0.0673	−0.45	0.6540
q_{23}	Emulation effect from group 2 on group 3	−0.2205	0.1509	−1.46	0.1540
q_{31}	Emulation effect from group 3 on group 1	0.0564	0.0355	1.59	0.1221
q_{32}	Emulation effect from group 3 on group 2	0.0195	0.0150	1.31	0.2002

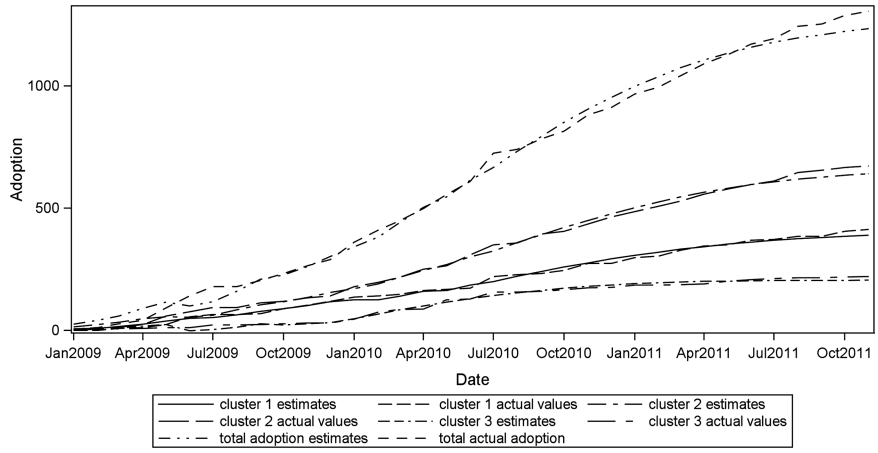

Figure 2 Model estimates versus real values in three groups of specialties.

or no common patients. This is reconfirmed by the fact that the coefficient of innovation (p_i) is very weak in every group, which indicates the inefficiency of relying entirely on marketing efforts. Figure 2 presents a comparison of the model estimates with real data.

Geographical proximity network effects

Table 4 shows the estimation results of equation (2) for the rural/urban clusters. The only significant effect in urban groups is the external effect, while in rural areas, not only are both external and within group effects strong, but also the effect from the urban group on the rural group is strong and statistically significant. Among physicians in rural areas, the within and between group effects (q_{22}, q_{12}) are stronger than the external effect (p_2) and thus hypothesis H2-2 is supported. Moreover, the effect of adoption by physicians in urban areas on physicians in rural areas (q_{12}) is stronger than the effect of adoption by physicians in rural areas on physicians in urban areas (q_{21}), and thus hypothesis H2-1 is also supported. Finally, among physicians in urban areas, the external effect (p_1) is stronger than the within and between group effects (q_{11} and q_{21}), and thus hypothesis H2-3 is supported. Figure 3 presents a comparison of the model estimates with real data.

CONCLUSIONS

This work is the first that considers HIE as a multisided platform and investigates the drivers of its adoption, leading to the development of the theoretical foundations for more advanced and in-depth analysis of HIE adoption and use. We expand the conventional Bass[28] model to consider the multi-group diffusion of HIE and the indirect network effects. This enables us to examine the interrelationships between drivers of HIE adoption and the resulting outcomes, which, to our knowledge, have rarely been considered together in the literature. We show how the findings of this research about direct (within group) and indirect (between groups) network effects of different groups of physicians on joining HIE systems can help RHIOs in designing marketing strategies to ensure growth. We also improve on existing research on HIE adoption by examining actual member behavior over time in a panel dataset. We use geospatial data analysis to better identify local diffusion effects and the role of physical location of physicians on HIE adoption. Finally, this work complements research on e-healthcare system adoption by leveraging acculturation of different groups of healthcare professionals in the context of e-healthcare systems.

HEALTHeLINK, the regional health information organization of our study, is currently supported by state, federal, and its stakeholders' funds. The patients have full control of their medical information; they determine who is allowed to access their record and can change their consent type at any time. As a public RHIO, HEALTHeLINK services are provided at no cost to physicians. However, the ultimate goal of RHIOs in the US is to become financially independent and generate revenues by charging the beneficiaries for the HIE services they receive; hence design of a sustainable business plan is of crucial importance for them. To do so, RHIOs should be fully aware of the complex relationships among their users and create pricing schemes accordingly. This work is the first step toward this direction. Presenting the strategies which have proven efficient in successfully increasing the HIE adoption by HEALTHeLINK and revealing the relative value that different physicians receive from HIE services depending on their specialty and their geographical location helps RHIOs to not only design pricing schemes, but also create effective marketing policies and growth strategies.

In contrast to previous findings, our results show that adoptions in different market segments are not equally and similarly affected by different sources of influence, and the network externalities between different groups of physicians are an important driver of HIE adoption. We show that physicians are more affected by the adoption of other physicians in similar specialty clusters since they share more common patients with them. Finally, our results show that the geographical location of physicians is a determining factor in their HIE adoption decision. Physicians who practice in rural areas are highly affected

Table 4 Estimation results for location based groups

Parameter	Description	Estimate	SE	t Value	$P_r > \|t\|$
p_1	Innovation effect in urban group	0.010086	0.00190	5.31	<0.0001
q_{11}	Emulation effect within urban group	0.003148	0.00160	1.96	0.0574
q_{21}	Emulation effect from rural group on urban group	0.078106	0.0393	1.99	0.0546
p_2	Innovation effect in rural group	0.015343	0.000250	61.43	<0.0001
q_{22}	Emulation effect within rural group	0.016824	0.000682	24.66	<0.0001
p_{12}	Emulation effect from urban group on rural group	0.057861	0.00290	19.97	<0.0001

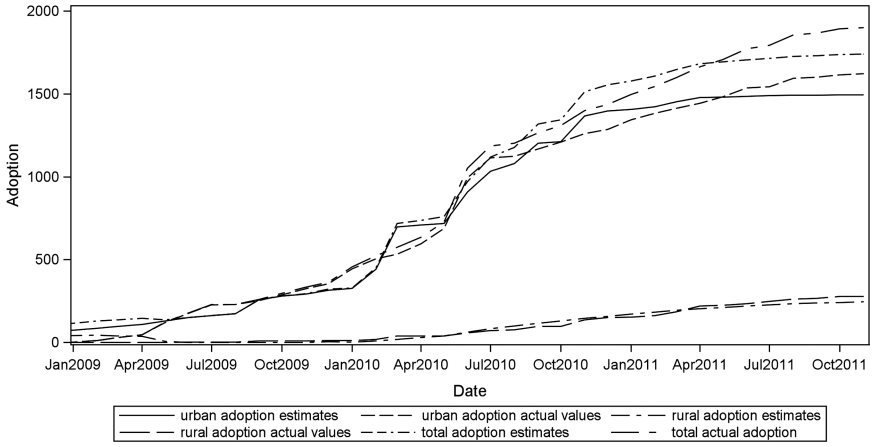

Figure 3 Model estimates versus real values in rural and urban groups.

by the adoption of those who are located in urban areas. The results of the analysis at practice level (see online supplementary appendix) are consistent with the physician level analysis results.

A limitation of this study is that it includes only one HIE and examines a relatively short time period for adoptions (35 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. Another limitation is that our model examines only provider adoption of HIE and does not consider the effects of clinical data sources (hospitals, labs, and radiology facilities) joining the HIE over time. In this context, this work initiates a productive line of research on HIE adoption and will serve as the foundation for further research as our experience with such systems grows over time.

Patient flows among specialties may be driven by a variety of factors such as rural/urban divide, affiliations with common hospitals, specialty size, and closeness of the medical specialties themselves, such as allergy and dermatology. Our objective is not to derive any relationships between these various factors and adoption; we focus only on patient flows and adoption. However, there may be a myriad of such factors underlying patient flows. A full-fledged investigation of these factors is a possible area for future research.

In this study, we only focus on between and within group effects on HIE adoption. Other than these effects, there are many other factors that affect the physicians' and practices decision to join HIE. The membership cost, perceived benefits of HIE for each member, and federal and state regulations, as well as the affiliations between physicians and hospital groups are among the many influential factors that affect HIE adoption. Further analysis of these factors and their effect on HIE adoption can shed considerable light on our understanding of HIE diffusion. We are currently pursuing some of these avenues.

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Contributors NY had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. Design and conduct of the study: NY, RR, RG, AYD. Acquisition and preparation of data: RS, RS, GS. Analysis and interpretation of the data: NY, AYD, RG, RR. Drafting of the manuscript: NY, RR. Critical revision of the manuscript for important intellectual content: RS, RR, GS. Administrative and academic support: RS. Study supervision: RR.

Competing interests RS and GS are affiliated to the Department of Family Medicine. The Department of Family Medicine has a contract with HEALTHeLINK to evaluate the impact of HEALTHeLINK's programs on quality of care and other outcomes, not related to this work.

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ONLINE SUPPLEMENT

PART 1: EXTENDED BASS MODEL

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 $\frac{f(t)}{1-F(t)} = p + qF(t)$ in which $f(t)$ is the probability of adoption and $F(t)$ is the cumulative probability of adoption until time t . The coefficients of innovation and emulation are indicated by p and q respectively. If m is the size of potential market, then Bass model can be rewritten as $\frac{dY(t)}{dt} = y(t) = \left(pm + qY(t)\right) \times (1 - F(t))$ in which $y(t)$ is the number of adoptions in time t and $Y(t)$ is the total number of adoptions until time t.

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 k separate but inter-linked groups as follows

$$f_i(t) = \left[p_i + \sum_{j=1}^{k} q_{ji} F_j(t)\right][1 - F_i(t)] \qquad (1)$$

Where q_{ji} captures the network effects. When $i = j$, q_{ji} is simplified as q_{ii} and captures the direct network effect within group i. When $i \neq j$, q_{ji} captures the indirect network effect from group j on group i. Note that when $n = 1$, the above model is reduced to the original Bass single-group linear model. Due to the fact that $\frac{dF_i(t)}{dt} = f_i(t)$ we can consider equation (1) as a first order differential equation and solve for $F_i(t)$ to derive a set of k simultaneous equations.

By (1), $\frac{dF_i(t)}{dt} = [p_i + \sum_{j=1}^{k} q_{ji} F_j(t)][1 - F_i(t)]$, which is

$$\int \frac{1}{[p_i + \sum_{j=1}^{k} q_{ji} F_j(t)][1 - F_i(t)]} dF_i(t) = t + D \text{, or}$$

$$\int \frac{A - AF_i(t) + Bp_i + B\sum_{j=1}^{k} q_{ji} F_j(t)}{[p_i + \sum_{j=1}^{k} q_{ji} F_j(t)][1 - F_i(t)]} dF_i(t) = t + D .$$

$$A + Bp_i + B \sum_{j=1, j\neq i}^{k} q_{ji} F_j(t) = 1 \text{ and } -A + Bq_{ii} = 0 .$$

$A = Bq_{ii}$ and $Bq_{ii} + Bp_i + B\sum_{j=1, j\neq i}^{k} q_{ji}F_j(t) = 1$.

$$A = \frac{q_{ii}}{p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t)} \text{ and } B = \frac{1}{p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t)}.$$

$$\int\left[\frac{\dfrac{q_{ii}}{p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t)}}{p_i + \sum_{j=1}^{k} q_{ji}F_j(t)} + \frac{\dfrac{1}{p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t)}}{1 - F_i(t)}\right]dF_i(t) = t + D$$ which can be simplified as

$$\frac{q_{ii}(1 - F_i(t))}{p_i + \sum_{j=1}^{k} q_{ji}F_j(t)} = e^{-(t+D)(p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))}$$ we can derive:

$$F_i(t) = \frac{q_{ii} - (p_i + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))e^{-(t+D)(p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))}}{q_{ii}(e^{-(t+D)(p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))} + 1)}.$$

Since $F_j(0) = 0$, $j = 1, \ldots, k$, we have

$$\frac{q_{ii} - p_i e^{-D(p_i + q_{ii})}}{q_{ii}(e^{-D(p_i + q_{ii})} + 1)} = 0, \text{ or}$$

$$-D = \frac{1}{p_i + q_{ii}} \ln \frac{q_{ii}}{p_i}.$$

Then

$$F_i(t) = \frac{1 - (\frac{p_i}{q_{ii}} + \frac{1}{q_{ii}} \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))e^{-(t - \frac{1}{p_i + q_{ii}} \ln \frac{q_{ii}}{p_i})(p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))}}{e^{-(t - \frac{1}{p_i + q_{ii}} \ln \frac{q_{ii}}{p_i})(p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))} + 1},$$

where $e^{-(t - \frac{1}{p_i + q_{ii}} \ln \frac{q_{ii}}{p_i})(p_i + q_{ii} + \sum_{j=1, j\neq i}^{k} q_{ji}F_j(t))}$ can be simplified as

$$e^{-(p_i+q_{ii}+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t))t+(p_i+q_{ii})\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t)\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}}$$

$$=\frac{q_{ii}}{p_i}e^{-(p_i+q_{ii})t+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t)(\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}-t)}.$$

Then

$$F_i(t)=\frac{1-(1+\frac{1}{p_i}\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t))e^{-(p_i+q_{ii})t+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t)(\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}-t)}}{\frac{q_{ii}}{p_i}e^{-(p_i+q_{ii})t+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t)(\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}-t)}+1}.$$

Which results in:

$$Y_i(t)=m_iF_i(t)=m_i\frac{1-(1+\frac{1}{p_i}\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t))e^{-(p_i+q_{ii})t+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t)(\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}-t)}}{\frac{q_{ii}}{p_i}e^{-(p_i+q_{ii})t+\sum_{j=1,j\neq i}^{k} q_{ji}F_j(t)(\frac{1}{p_i+q_{ii}}\ln\frac{q_{ii}}{p_i}-t)}+1} \qquad (2)$$

In equation (2), $Y_i(t)$ is the total number of adaptors in group i at time t. It is affected by both external sources, p_i, and the number of adaptors until time t in not only group i but also other groups $(j \neq i)$, and thus captures both direct and indirect network effects

PART 2. DETAILS OF DATA SETS AND METHODS

Multi-dimensional Scaling and Ward Clustering

The patient flow may be affected by organizational factors such as similar affiliations of the doctors. However, the decision to refer a patient is made in two stages: first, a doctor decides about the specialty to which a patient should be referred based on the patient's medical condition; next, he decides about the doctor with that specific specialty to whom the patient should be referred. Choosing the "specialty" for referring a patient is based on patients' medical necessities and needs. Physicians' affiliations to common practices only affect the second stage of patient referral decisions. We group "Specialties" rather than individual physicians, which in part eliminates the possible confounding factors such as similar affiliations. Furthermore, our approach of clustering by specialties rather than clustering by practices results in generalizable insights about the effects of specialties on each other in HIE adoption. These clusters and their interlinked effects can easily be used by RHIOs and other HIE affiliated organizations to promote HIE through targeted marketing efforts.

Patient flows among specialties may be driven by a variety of factors such as rural/urban divide, affiliations with common hospitals, specialty size, and closeness of the medical specialties themselves such as allergy and dermatology for instance. Please note that our objective is not to derive any relationships between these various factors and adoption; we focus only on patient flows and adoption. However, there may be a myriad of such factors underlying patient flows.

In order to identify the clusters of specialists with highest ratio of common patients between them, we first construct a matrix of specialties in which each element of matrix shows the ratio of common patients between the two specialties. Specialties with high ratio of common patients are the ones that have the highest flow of patients between each other. Based on this matrix, we applied Multi-dimensional Scaling (MDS) to create three artificial dimensions for each specialty such that the artificial distance between the two specialties based on these dimensions are correlated as highly as possible with the real common patients' ratio between them.[51,52] These dimensions were then used to construct 3 clusters of specialties. We used the Ward minimum-variance clustering method. The minimum variance method is designed to generate clusters in such a way as to minimize the within cluster variance. In this method, the distance between two clusters is the ANOVA sum of squares between the two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generations.[53–55]

Figure 3 shows the relative position of 21 specialties in an artificial three dimensional space. The closer the specialties are, the higher is the common patient ratio between them. Table 3 presents the complete list of specialties within each cluster. We used PROC MDS and PROC CLUSTER in SAS to conduct MDS analysis and Cluster specialties accordingly.[54] For a complete review of the methods applied on this data set see Yaraghi et al.[41]

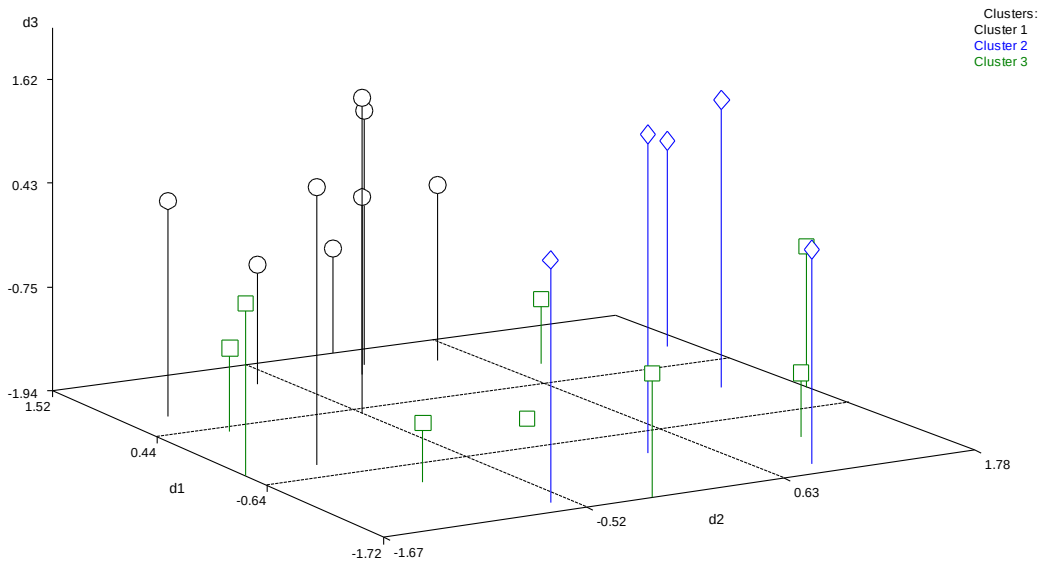

Figure 3. Cluster of specialties based on common patients

We also clustered practices based on the two dimensions of latitude and longitude. Since we already have two real dimensions for clustering, we do not need to produce any more dimensions by MDS analysis and can directly apply clustering methods. Figure 4 shows the 2 clusters of practices based on their geographical location. The practices shown with black stars are the ones which are concentrated in urban areas of western New York and while the ones shown with blue stars are the practices which are farther from each other and are located in rural areas.

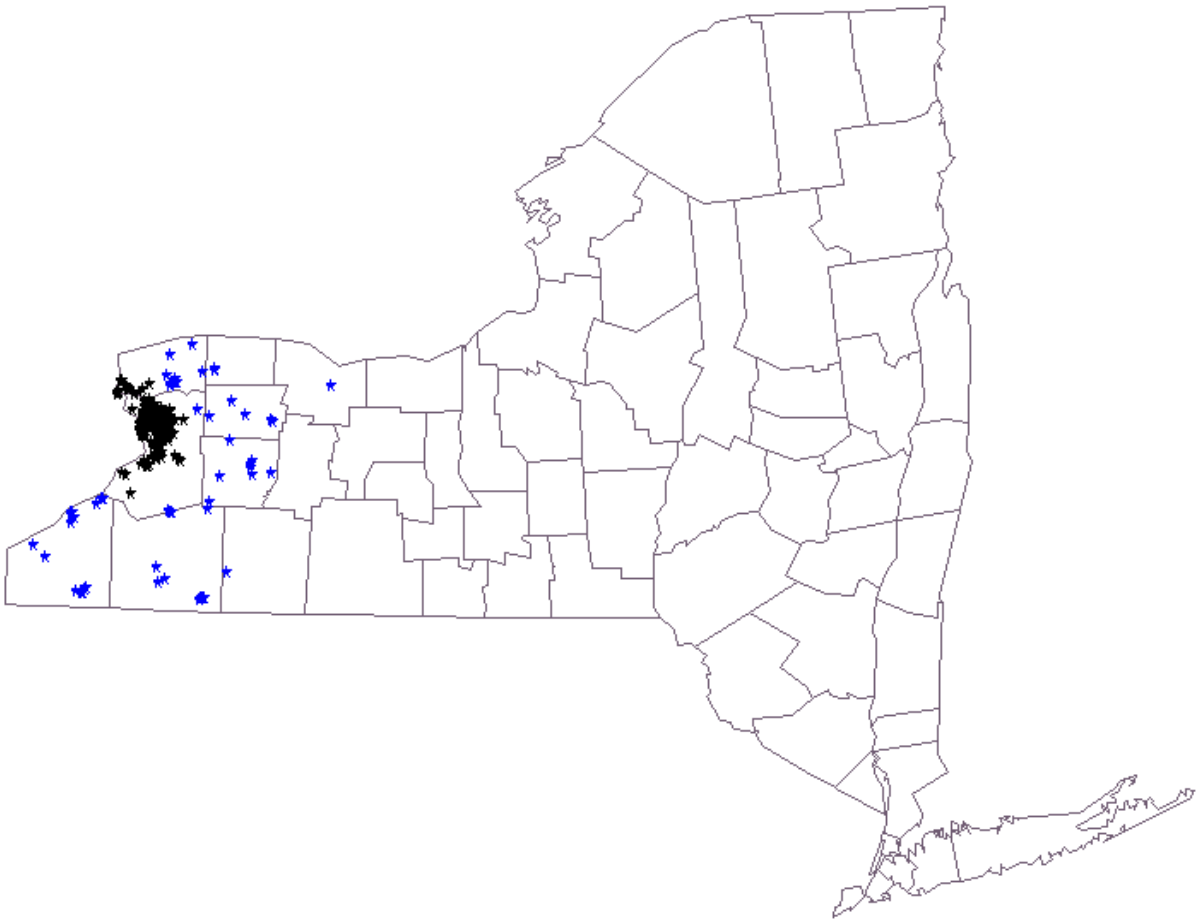

Figure 4. clusters of practices based on their latitude and longitude

Nonlinear three stage least squares method

After identifying different clusters, the sets of equations in (2) are estimated jointly using the nonlinear three-stage least squares option of MODEL procedure in SAS software. For studying the effect of specialty groups, equations in (2) will be a set of 3 different simultaneous equations $(i = 1,2,3)$ while for examining the effects of geographical location, since we have two groups of urban and rural locations, equations in (2) will be a set of 2 different simulations equations$(i = 1,2)$. 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 & Theil[56] 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 random errors.[57] Nonlinear least squares method has been shown to produce more efficient estimates in the context of the Bass diffusion model.[58]

	Cluster	Cluster Name	Specialty
1	1	medical and surgical subspecialties (especially cardiac)	INTERNAL MEDICINE - CARDIOVASCULAR DISEASE
2			INTERNAL MEDICINE - ENDOCRINOLOGY DIABETES & METABOLISM
3			INTERNAL MEDICINE – GASTROENTEROLOGY
4			INTERNAL MEDICINE - HEMATOLOGY & ONCOLOGY
5			OTOLARYNGOLOGY
6			PEDIATRICS
7			RADIOLOGY
8			SURGERY
9	2	primary care and women's health	ADULT MEDICINE
10			ALLERGY & IMMUNOLOGY – ALLERGY
11			FAMILY MEDICINE
12			INTERNAL MEDICINE - INFECTIOUS DISEASE
13			WOMEN'S HEALTH
14	3	medical and surgical subspecialties (especially renal, neurological, and musculoskeletal)	INTERNAL MEDICINE - GERIATRIC MEDICINE
15			INTERNAL MEDICINE – NEPHROLOGY
16			INTERNAL MEDICINE - PULMONARY DISEAS
17			INTERNAL MEDICINE – RHEUMATOLOGY
18			ORTHOPEDICS
19			PSYCHIATRY & NEUROLOGY – NEUROLOGY
20			PSYCHIATRY & NEUROLOGY – PSYCHIATRY
21			UROLOGY

Table 3: Cluster Members

PART 3: ANALYSIS OF ADOPTION AT PRACTICE LEVEL

We have also analyzed the effects of patient flow on HIE adoption at practice level. We have followed a very similar clustering approach as described in previous section to group practices into 3 different clusters based on their common patients. In each cluster, the ratio of common patients between practices is high while the ratio of common patients between practices in two different clusters is low. Following the same argument about the strong effects of patient flow on deriving HIE adoption, we expect to see strong within group effects and weak between group effects in HIE adoption at practice level.

Parameter	*Description*	*Estimate*	*Std. Err.*	*t-value*	$P_r > \|t\|$
q_{11}	emulation effect within group 1	0.064273	0.0215	2.98	0.0061
q_{22}	emulation effect within group 2	0.05915	0.0261	2.26	0.0321
q_{33}	emulation effect within group 3	0.056531	0.0163	3.48	0.0018
p_1	innovation effect in group 1	0.025945	0.000966	26.87	<.0001
p_2	innovation effect in group 2	0.015332	0.00573	2.67	0.0128
p_3	innovation effect in group 3	0.021859	0.0114	1.92	0.0654
q_{12}	emulation effect from group 1 on group 2	0.009138	0.00316	2.89	0.0077
q_{13}	emulation effect from group 1 on group 3	0.009636	0.00165	5.85	<.0001
q_{21}	emulation effect from group 2 on group 1	0.017105	0.00906	1.89	0.0702
q_{23}	emulation effect from group 2 on group 3	0.042804	0.0837	0.51	0.6132
q_{31}	emulation effect from group 3 on group 1	0.034059	0.0377	0.90	0.3748
q_{32}	emulation effect from group 3 on group 2	0.017038	0.00499	3.41	0.0021

Table 4: The estimation of HIE adoption model at practice level

Table 4 shows the results of the model estimation at practice level. The within group emulation effects shown by q_{11}, q_{22} and q_{33} are all positive and significant at 5% level. Some of the between group effects are also significant. However, the magnitude of the between group effects are much less than the within group effects. These results are consistent with our main findings and confirms positive effects of common patients on HIE adoption.

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