Impact of Health Information Exchange Adoption on Referral Patterns

Abstract

Efforts to promote Health Information Exchanges (HIE) on a nationwide scale are beset with major challenges and one of them is its meaningful use for both physicians and patients. Referrals potentially provide a context for the meaningful use of HIE and we are yet to understand how HIEs affect referrals. This research studies the impact of HIE on referral patterns. We establish that participation in an HIE network increases the referrals sent to and received from other HIE participants. We investigate this relationship using both econometric and network-analytic methods. While the econometric analysis focuses on the underlying associations between HIE adoption and referral patterns, the network analysis addresses the transformation process by which HIE adoption and referrals co-evolve over time. This study has significant implications for healthcare policy-making, development of innovative HIE business models, and management of healthcare organizations.

Keywords: Health Information Exchanges, Referrals, HIE Adoption, Referral Decision-making

1. Introduction

Referrals are an integral part of the US healthcare system. More than a third of the patients in the US are referred to specialists each year (Mehrotra et al., 2011). Referrals have been shown to significantly impact the cost and clinical quality of healthcare services[1] (Schmidt et al. 1998, Boulware et al. 2006, Fritz et al. 2012). Prior research highlights the importance of communication and coordination among the service providers and hence, the maintenance of continuity of care among them as critical success factors for effective referral management (Bodenheimer, 2008; Forrest et al., 2000; Hofmarcher et al., 2007; O'malley & Reschovsky, 2011; B. H. Starfield et al., 1976). Referral management involves sharing care-related information among physicians in addition to a host of other important administrative services such as

[1] For a simple example, if a patient is referred to a doctor who does not have the proper access to the patients' latest and complete medical history, then, the referred doctor may order tests which may have already been done at another point of care. This results in unnecessary costs for the patient and the healthcare system.

providing service-provider databases, enabling electronic communication among referral coordinators, making referral appointments and scheduling follow-up visits to name a few (Ramelson et al., 2018). By design, the recently emergent notion of a referral management system is intended to facilitate referrals by serving as efficient intermediaries between physicians in a referral process[2].

Health Information Exchanges (HIE) are web-based portals that are intended to enable healthcare providers involved in the continuum of patients' care to access and share all relevant clinical information of the patients electronically. HIE platforms have been integral to the US healthcare reforms since the time of enactment of the Health Information Technology for Economic and Clinical Health Act (Vest & Gamm, 2010). By design, a HIE platform is a repository of patients' care information and does not provide other major administrative services needed in referral management. In contrast to referral management systems that are designed to impact referral behaviors of physicians, it is therefore not clear whether a HIE platform by itself could exert such similar impact. Put formally, the fundamental research question of this study is: *Does HIE adoption change the referral patterns of physicians?*

The central contributions of this research are threefold, and are summarized as follows. First, while extant HIE literature has focused almost entirely on the effect of HIE adoption on *healthcare outcomes* such as reductions in emergency room visits, hospital re-admissions, lengths of stay and diagnostic tests (Boockvar et al., 2017; Eftekhari et al., 2017; Jung et al., 2015; Murphy et al., 2017; Vest et al., 2014; Vest et al., 2015), to the best of our knowledge, the effect of HIE adoption on *healthcare processes* has not been addressed. In particular, referral is one such process which is important in itself and merits in-depth investigations in the context of HIE adoption. We address this importance as follows. HIE segments the physician market into adopters and non-adopters. Referrals among physicians can occur either exclusively within each segment or across the two segments. Our research question therefore translates to whether the advantages of HIE would induce a shift in the quantity of referrals occurring across the segments into

[2] https://365.himss.org/sites/himss365/files/365/handouts/552578704/handout-260.pdf
https://learn.par8o.com/hubfs/The%205%20Componentse%20of%20Successful%20Referral%20Management%20-%20par8o.pdf

referrals within the segment of adopters. In effect, this shift would amount to a cannibalization of referrals occurring across the segments by the adopter segment. This would also reveal a balkanization of the physician market into *technology-haves* and *have-nots* where the haves benefit at the cost of have-nots. In this research, we show that physicians, upon adoption of HIE, prefer to refer their patients to other physicians who have also adopted, indicating a potential for balkanization of the physicians' market.

Second, although we do not propose a comprehensive model of the referral decision making process in general, we establish that HIE is a significant factor in this process by concomitantly taking into account other known factors that could potentially impact referrals.

Third, we employ dynamic network analysis as a comprehensive framework to examine the interplay of HIE adoption and referrals and model their mutual effects. To the best of our knowledge, this is the first study in the literature on information systems that uses dynamic network analysis to examine the mutual effects of the adoption of an IT innovation and its application.

The overall research approach in this study is summarized as follows. Based on the extant literature on physicians' referral processes and the HIE benefits, we conceptualize a mechanism to explain how HIE can improve referral processes and consequently drive its members towards referring to other HIE members. This mechanism provides the logic underlying the referral decisions of physicians. Based on this mechanism, we formulate research hypotheses and empirically test them using publicly available data. These datasets have been obtained from the Centers for Medicare and Medicaid Services (CMS) and HEALTHeLINK, a Regional Health Information Organization in Western New York. More specifically, the CMS datasets present annually aggregated number of referrals from one physician to another and the HEALTHeLINK dataset presents their dates of adoption. While these datasets enable us to properly test our research hypotheses, they do not allow us to fully test the underlying proposed mechanism. To address this limitation, we conducted an exploratory field study using interviews with HIE members. The field study has confirmed our proposed mechanism and also yielded significant insights and reasons for some of the unexpected findings from the empirical study.

The organization of this paper is as follows. Section 2 reviews the literature on state-of-the-art in HIE platforms. Section 3 develops the research hypotheses. Section 4 develops the econometric models to test the hypotheses and Section 5 analyzes the mutual effects between HIE adoption and referrals. Section 6 presents the empirical findings. Section 7 presents the exploratory field study and its findings. Section 8 concludes with a discussion on the findings of this study, its limitations and directions for future research.

2. Related Literature

We review the literature on HIE first, and then the literature on referral decision making. The extant research on HIE adoption and usage can be grouped into two categories. The first category consists of research that examines the antecedents of HIE adoption and drivers of its use. The second category consists of research that examines the consequences of HIE adoption and usage. In the following, we provide an overview of the recent literature in these categories and discuss how our research contributes to the current literature.

Modeling the HIE system as a multisided platform, Yaraghi et al. (2013) examine the rates of HIE adoption by the primary-care and specialist physicians. They model the underlying diffusion processes due to network cross-externalities by generalizing the well-known Bass diffusion model. Yaraghi et al. (2014b) extend this analysis to adoption behaviors across rural and urban geographical domains and several medical specialty groups. Furthermore, Yaraghi et al. (2014a) study how adoption, usage and the involvement of clinical practices in the co-production of HIE services are impacted by the interactions in the network of physicians and the network of patients. They demonstrate the effects due to the networks of physicians and patients, the isomorphic effects of large practices on smaller practices, and practice labor inputs on HIE usage. The effect of other factors such as competition and privacy regulations on the growth of HIE platforms have also been extensively studied by other researchers (Desai, 2014; Miller & Tucker, 2014).

The other stream of research is focused on the consequences of HIE adoption and use. A significant number of studies have proposed that HIE platforms can help medical providers make better decisions, save more lives, and reduce costs (Frisse et al., 2012; Overhage et al., 2005; Vest et al., 2015; Walker et al., 2005). Specifically, prior studies have shown that HIEs can reduce medical expenditure (Adjerid et al. 2018), unnecessary medical procedures (Lammers et al., 2014; Yaraghi, 2015), repetition of diagnostic imaging and testing (Bailey et al., 2013), and repetition of therapeutic procedures (Eftekhari et al., 2017). All of these studies are entirely focused on the impact of HIE on healthcare outcomes. Contrastingly, the current research focuses on the impact of HIE on referral processes as one the major processes in healthcare delivery.

A significant stream of studies on referral decision making is focused on exploring the factors that impact the decision on whether to refer or not, and as a result, explaining the variation in referral rates among physicians (Forrest et al., 2002; Forrest et al., 2006; Langley et al., 1997; B. Starfield et al., 2002). Access to hospital facilities, remoteness from specialist care and the primary care physicians' relationship with specialist consultants appear to be important non-medical factors affecting referral decisions (Langley et al., 1997). Another stream of research on referrals has examined the factors that impact the choice of physicians to refer to. Type of illness, medical skills of physicians, previous experience with physicians, patient preferences, proximity to the patient's home, and how quickly the patient could be seen by the consulting physician have been reported as important factors that impact the choice of the physicians in a referral process (Barnett et al., 2012; Forrest et al., 2002; Javalgi et al., 1993; Kinchen et al., 2004). Javalgi et al. (1993) have shown that in a referral process, physicians usually consider technology factors (such as shared electronic patient records or other factors that facilitate communications), service factors (such as those that show previous experience with the doctors), cost, and patient access. To the best of our knowledge, the impact of HIE on referral decision making has not been discussed in the literature.

3. Effects of HIE Adoption on Referral Patterns

In the following, we first identify the ways in which an HIE platform could improve referral processes, based on the literature on the general benefits of HIE to healthcare systems. Next, we conceptualize a mechanism through which an HIE platform drives its participants towards referring to the other participants. This conceptualization is a conjunction of the general benefits of HIE to referral processes and the specific functionalities of the HIE platform.

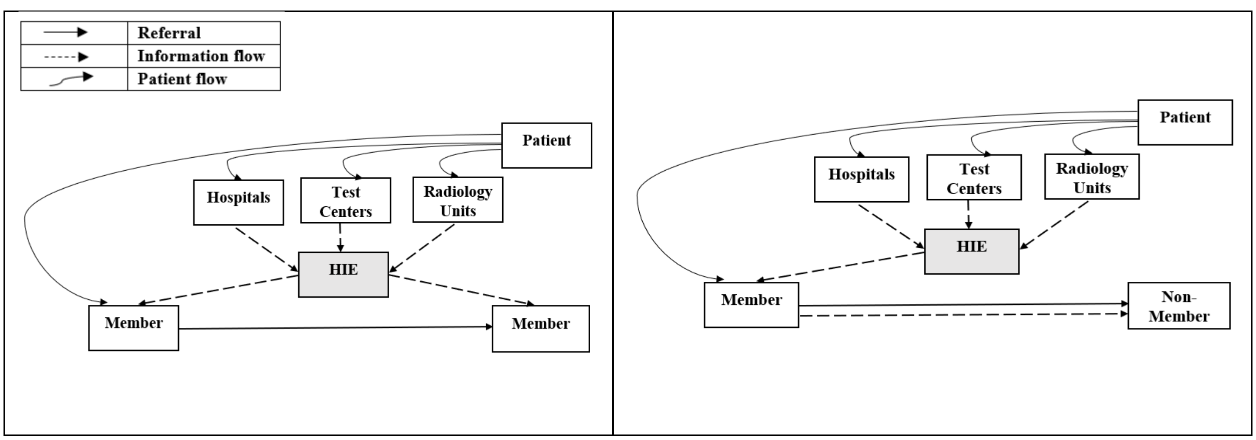
HIE Impact on Referral Processes: Recent research has shown that appropriate integration of HIE technology into the practices' workflows can significantly reduce the amount of administrative work (Fecher et al. 2020). Specifically, HIE helps to decrease the paperwork involved in a referral process (Fontaine et al., 2010) by improving the access to test results and facilitating the processing of medical claims. Through HIE, healthcare providers have access to the results of medical procedures that were performed previously for the patients (Vest et al., 2015). Accessing this information prevents the duplication of tests, redundant collection of information from the patients, and possible treatment and medication errors. As a result, HIE improves the efficiency and soundness of the services provided by a physician. There is an abundance of literature that documents the significant effect of post-discharge and follow-up visits with primary care physicians on increasing the quality of care (Avlund et al. 2002, Sharma et al. 2010). By providing instant access to medical records that were created during visits to hospitals or in hospitalization periods, HIEs enhance the quality of follow-up visits to the physicians (Van Walraven et al. 2002).

Proposed Mechanism: An HIE mainly provides data on diagnostic and therapeutic test results from test centers, radiology reports from radiology units, and records of visits, stays, and in-patient and out-patient treatments from hospitals. In addition, HIE provides a service to update its participants on the patients' hospital admission, discharge and transfer (ADT). The ADT notification is sent to concerned HIE members as soon as their patients visit an Emergency Department, or get admitted, discharged or transferred from a hospital in the region. The ADT notification can be managed and customized by the HIE members according to their own workflow needs and preferences (Fecher et al., 2020).

In the following, we argue how HIE minimizes the transaction costs and the possible frictions associated with making a referral when both the physicians are members of the HIE. Figure 1 presents the patient flow and the information flow involved in a referral process using a HIE. Figure 1(a) shows a referral from a member to another member, and Figure 1(b) shows a referral from a member to a non-member. The referred physician, at the time of seeing the patient, should have access to the patient's test center records, radiology reports, hospital records and the hospital ADT. As can be seen from Figure 1(a), this information is immediately available from the HIE; however, as Figure 1(b) shows, this information should be deliberately sent by alternate channels by the referring physician. These alternate channels could be either through hardcopies that are hand-carried by the patient, or at best, through an exchange between the EMR systems of the referring and referred physicians if they are both interoperable and inter-connected. Furthermore, in the absence of a centralized HIE, the patient records from the multiple sources could be fragmented and distributed at different points of care (Alshawi et al., 2003). Therefore, the responsibility of assembling these records from diverse sources and ensuring a *complete, most recent and accurate* and *timely* information transfer to the referred physician almost entirely rests with the referring physician. When referrals are made, referring physicians must coordinate service delivery across multiple settings and providers to maintain an efficient continuum of care. The integration of patient information in this process is complex and time-consuming (Forrest et al., 2000). All of these render the alternate channels to be less efficient and less reliable than a centralized HIE. As a result, they could induce a significant additional transaction cost to the referring physician when the HIE is not used. Hence, a member-physician is both administratively and transactionally motivated to refer to other HIE members. Therefore, this motivation leads to an increase in the number of referrals to HIE members. Correspondingly, given a fixed load of patients to refer, this will result in a decline in the number of referrals to non-members.

Note that non-member referring physicians could also avail the HIE benefits of referring patients to member-physicians since the referred physicians would any way have access to all these records from the HIE. However, the referring physicians, by virtue of being non-members, will not be as cognizant of this value as the members. Thus, we do not expect the non-members to take HIE into consideration when making referral decisions. Consequently, any referrals from non-members to members cannot be as a result of the realization of HIE benefits by the referring physicians. This implies that a physician's decision to refer intentionally to member-physicians can occur mainly after the referring physician's HIE adoption.

The above mechanism can be positioned within the typology of mechanisms described in (Rivera et al., 2010). They explain changes in social networks using three perspectives: *Assortative*, *Relational* and *Proximity*. The assortative perspective is based on compatibilities and complementarities among network entities, the relational is based on network distance among the entities which would impact trust, belief etc., and proximity pertains to distance in time and space. Correspondingly, Rivera et al. (2010) classify mechanisms into specific buckets according to these perspectives. Our context is the network of physicians where links and their strengths could be defined by the quantity of referrals. In our study, we measure shifts in referrals on an annual basis. We argue that the mechanism for these shifts is assortative, and the HIE members shift their referrals more to other HIE members as a result of their mutual compatibility offered by their HIE membership. This compatibility among members is due to their ability to share and benefit from the services of the HIE. The referral shifts could not occur as a result of any other relational or proximity mechanisms for the following reasons. First, building relational network connections takes much longer and second, geographical changes occur much less frequently in our context. Assuming that the existing network relationships and the proximity among physicians remain fairly steady during the period of our study, we therefore explain the shifts in referrals as essentially due to the compatibility component yielded by HIE.



(a) Member to member referral (b) Member to non-member referral

Figure 1. Patient flow and information flow in HEALTHeLINK

Given the above arguments, we expect that once physicians adopt HIE, they take HIE into consideration in their referrals, and thus shift their referrals from non-members to members. We thus develop the following hypotheses to test this argument:

H_1: *HIE adoption increases the number of referrals to other HIE members.*

H_2: *HIE adoption decreases the number of referrals to non-HIE members.*

Recall that the referring physicians have to ensure that complete, up-to-date and accurate information is transferred in a timely manner to the referred physicians. HIE provides a more efficient and reliable technology for such transfer than the alternate traditional channels and hence, incurs lower transaction costs to the referring physicians. Now, consider physicians who receive referrals from others. When physicians receive referrals through the alternate channels, a part of these transaction costs incidentally gets passed to the referred physicians. For example, if a referred physician receives incomplete information on a patient, then it would entail additional administrative work on their end to follow up with the referring physician's office and other test centers to ensure data completeness. Further, upon patients' arrival at the referred physician's office, if the required service to the patient is delayed due to the incompleteness of the medical data, it would also lead to patients' annoyance and some friction. Thus we argue that the receiving member-physicians would prefer to receive referrals through the HIE channel which is more efficient. This preference leads to a prioritization of HIE members over non-members, resulting in an increase in the number of referrals received from HIE members. Under the reasonable assumption that the referral-receiving capacity of physicians is limited, this preference leads to a corresponding decline in the number of referrals received from non-members. These observations are presented in the following hypotheses:

H_3: *HIE adoption increases the number of referrals received from HIE members.*

H_4: *HIE adoption decreases the number of referrals received from non-HIE members.*

The above discussion shows that H_3 is a natural corollary to $H_{1,}$ and H_4 follows H_3 under the reasonable assumption. Hence, testing H_3 and H_4 would provide additional empirical evidence for the validation of the proposed mechanism underlying H_1 and H_2.

4. Model and Estimation

To test our research hypotheses, we employ a Difference in Differences (DID) analysis. In the following, we first introduce our datasets and then present the model specifications.

4.1 Data Sources and Schema

We use four publicly available datasets in this research. The first two datasets, *Annual Physician Referrals* and *Physicians Compare*, are both provided by Centers for Medicare and Medicaid Services (CMS). *Annual physician referral* data indicates the number of Medicare patients referred by each physician to another, per year. *Physician compare* data includes physicians' characteristics such as specialty and affiliation. The third dataset, *HIE enrollment*, is provided by HEALTHeLINK. Healthcare providers join HEALTHeLINK at the practice level and can access the medical data of over 1.3 million patients through its database[3]. *HIE enrollment* data shows the data of adoption of HIE members. Finally, the fourth dataset is from *US National Census* and we use it to determine if a medical provider is located in a rural or urban area.

The final dataset for our analysis has been prepared as follows. First, using the National Provider Identifier (NPI), we matched the *annual physician referrals* data with *physicians compare* data for those physicians who practice in Buffalo, New York. We then merged the resulting dataset with *HIE* enrollment and *Census* data using the names and addresses of the physicians.

Our target population in this study is comprised of the physicians in Buffalo, NY which is one of the major Hospital Referral Regions (HRR) in Western New York. HRRs represent regional health care markets for primary, secondary and tertiary medical care. Our dataset pertains to medical providers in this HRR because HEATHeLINK mainly provided its services to this particular geographical area during the period of our study. Furthermore, referrals are mostly made within the same geographical area (Klein et al. 2014). Our data shows that more than 98% of referrals initiated by physicians in the Buffalo HRR are to other

[3] To access the available data on the HIE, most members use their own interoperable electronic medical records systems. The members can also manually download data through either a portal called *Virtual Health Records* or a web service called *ClinicalDocs.* Both these services are provided by HEALTHeLINK (Yaraghi et al., 2014b).

physicians within the same region. The final dataset consists of the attributes at both the physician and practice levels over the period 2009-2012. We note that the data pertains to Medicare patient referrals only.

4.1. Model Specification

We employ the DID method to test our hypotheses. DID attempts to mimic an experimental research design using secondary data, by studying the differential effect of a treatment on a 'treatment group' versus a 'control group' in a natural experiment (Angrist & Pischke, 2008). The DID approach has been used in a variety of contexts in Information Systems (Greenwood & Agarwal, 2015; Greenwood & Wattal, 2017).

Table 1. Description of the Outcome Variables

Notation	Description
NS^{HIE}	Number of referrals sent to HIE members (used in H_1)
NS^{No-HIE}	Number of referrals sent to non-HIE members (used in H_2)
NR^{HIE}	Number of referrals received from HIE members (used in H_3)
NR^{No-HIE}	Number of referrals received from non-HIE members (used in H_4)

Testing H_1-H_4: The outcome variable corresponding to each hypothesis is described in Table 1. The outcome of interest in each hypothesis is a count variable. For testing each hypothesis, we apply a generalized regression model assuming that the outcome has a Poisson distribution. The Poisson model yields a fully robust estimator for a two-way fixed effects specification (Wooldridge, 2010). For a proper statistical inference from any count model, an exposure variable defined as the period of time or area of space in which the counts are generated should be identified. This exposure variable modifies each observation from a count into a rate. Hence, the DID specification for testing H_1-H_4 is as follows.

$$ln(y_{ijt}) = \alpha_{1t} + \gamma_{1i} + \beta_1 HIE_{jt} + ln(N_{ijt}) + \varepsilon_{1ijt} \quad (1)$$

In equation 1, y_{ijt} is the outcome of interest measured for physician *i* belonging to practice *j* in year *t*. HIE_{jt} is the main independent variable and is equal to 1 if practice *j* has adopted HIE by year *t* and 0 otherwise. Time and physician fixed effects are denoted by α_{1t} and γ_{1i}, respectively. N_{ijt} denotes the exposure variable, and $ln(N_{ijt})$ is the offset variable needed to account for the exposure. The exposure variable is equal to total sent referrals by physician *i* belonging to practice *j* in year *t*, when testing H_1 and H_2. Similarly, for testing H_3 and H_4, it is equal to total received referrals by physician *i* belonging to practice *j* in year *t*. By definition, the coefficient of $ln(N_{ijt})$ is equal to 1 in Eq.1. β_1 is DID estimator and ε_{1ijt} denotes the error term. For estimating equation 1, we employ the procedure *proc genmod* in SAS (Pedan, 2001).

The Poisson model is most appropriate for modeling count outcomes. However, for robustness check, we further test each hypothesis using the Ordinary Least Square (OLS) regression model as in equation 2. The variables in equation 2 are defined similarly as in equation 1.

$$ln(y_{ijt}) = \alpha_{2t} + \gamma_{2i} + \beta_2 HIE_{jt} + ln(N_{ijt}) + \varepsilon_{2ijt} \tag{2}$$

Our proposed DID specification is similar to the one proposed in Bertrand and Mullainathan (2003). They study the effects of anti-takeover law which are implemented over different points in time at different states. The staggered passage of the anti-takeover laws means that the control group is not restricted to states that never passed these laws. Instead, the control group includes all the firms incorporated in states not passing an anti-takeover law at time t. Similarly, in our case, the treatment, which is HIE adoption, happens at different points of time during the period 2009-2012.

The proposed specification includes time fixed effects and unit fixed effects, which allow us to control for any time-specific and cross-sectional-invariant factors as well as unit-specific and time-invariant factors. Yet, the most important challenge with our DID specification is the fact that HIE adoption is endogenous. Many factors could affect the decisions of practices to self-select into adopting HIE. This violates the exogeneity of treatment which is a required condition for DID analysis. This is closely related to the common trends assumption which states that in the absence of treatment, the difference between the outcomes in the treatment and control groups should remain constant. In the following, we provide the details of our empirical strategies for addressing the endogeneity of HIE. Then, in Section 6, following the presentation of the results, we present a variety of tests for checking the common trends assumption, and probing the potential outlier effects that can arise due to the different timings of treatments.

Addressing Endogeniety: In order to ensure that differences in outcomes can be correctly attributed to HIE adoption, we prune the treatment and control groups such that the observed features of members of the two groups are as similar to each other as possible. We employ the Coarsened Exact Matching (CEM) procedure to limit the pre-treatment differences between the treatment and control groups (Iacus et al., 2012).

CEM is a non-parametric matching method introduced to avoid the confounding influence of pre-treatment control variables, and thus improves the causal inference when it is impossible to do a controlled field experiment (Berta et al., 2017). After pruning our sample using the CEM method and limiting the observations in the control and treatment groups to those that are as similar to each other as possible, we implement DID on the resulting matched sample to estimate the impact of HIE adoption. Using CEM in combination with DID analysis considerably reduces the bias from endogeneity when making causal inferences (Ho et al., 2007). When DID approach is combined with CEM, even if treated units differ in important unobserved characteristics from those in the control group, as long as such differences between the control and treatment groups do not vary over time, the fixed-effects specification can remove the bias resulting from such differences (Khurana et al., 2019).

We match the two groups of practices on their observable attributes by applying the CEM macro in SAS (Berta et al., 2017). These attributes could potentially impact HIE adoption. The description of the variables used in CEM is presented in Table 2. Each practice in the treatment group is matched to one practice in the control group. After matching, the differences in the covariates among the two groups are checked using *t*-test to ensure a balanced structure between the two groups.

The empirical results obtained from the DID models and associated tests and robustness checks are fully presented in Section 6.

Table 2. Description of the Variables Used in CEM

Notation	**Description**
NOP	Number of providers affiliated with a practice; indicates the size of the practice.
ERX	Binary; equals one if the practice is participating in the Medicare Electronic Prescribing Incentive program, and zero otherwise. This program encourages physicians and other professionals to use electronic prescribing to improve communication, increase accuracy, and reduce errors.

EHR	Binary; equals 1 if the practice participates in Electronic Health Records (EHR) program and 0 otherwise.
PQRS	Binary; equals one if the practice is participating in PQRS, and zero otherwise. This program encourages physicians and group practices to report information on the quality of care to Medicare. The PQRS gives participants the opportunity to assess the quality of care they provide to their patients and ensure that they get the right care at the right time.
Urban	Binary; equals one if the practice is located in an urban area, and zero otherwise.
Degree Centrality[4]	Degree centrality in a network of practices where each node represents a practice and a link denotes the number of common providers between a pair of nodes.
Isomorphic Quotient	Defined for a practice as the percentage of its physicians who are shared with larger practices.

5. Mutual Effects of HIE Adoption and Referrals

In the following we further study the dynamics of physicians' referrals and HIE adoption decisions. Yaraghi et al. (2014a) define a directed network where each node represents a practice and an arc from a practice *i* to practice *j* exists if practice *j* receives some patients from practice *i.* They show that practices with higher number of arcs coming from member-practices adopt HIE sooner than the others. As an extension of their study and confirmation of their findings, we apply survival models using our dataset to test whether the odds of receiving referrals from HIE members impacts the time to adopt. Next, to investigate the mutual association between HIE adoption and referrals we develop a network analysis using the Simulation Investigation for Empirical Network Analysis (SIENA). SIENA is a statistical tool which allows one to model longitudinal data on network and individual attributes simultaneously (Ripley et al., 2011; Snijders et al., 2010). SIENA uses simulations to study the joint evolution of multiple phenomena over time. SIENA by itself does not yield causal inferences among the variables studied and needs to be supported by further results from the discipline. In our context, the SIENA model provides an alternate modeling framework of the phenomenon studied using a network analysis perspective. This alternate perspective yields a significant robustness check for the main analysis from a distinctly different modeling approach. We consider the referrals among physicians as a directed network in which a node represents a

[4] Additional notes on degree centrality and isomorphic quotients: Degree centrality measures the exposure of a practice to other practices through sharing providers; isomorphic quotient measures the extent of influence that other practices may have on a given practice; each of these measures could potentially impact HIE adoption decisions. Practices with higher degree centrality tend to have more communication with other practices and this would have an impact on their HIE adoption decisions. Practices with higher isomorphic quotient could be more influenced by opinion leaders. Rogers and Kincaid (1981) have shown that adoption of innovations by opinion leaders could significantly affect the adoption decisions of others. In particular, smaller practices that share more physicians with larger practices tend to follow the HIE adoption decisions of the larger practices (Yaraghi et al. (2014a)).

physician and a link indicates a referral from a physician to another. Using SIENA, we are able to jointly test the impact of HIE adoption on the referral network, and vice versa. Our findings establish a mutual relationship between the referral network and HIE adoption. We describe these analyses in the following discussion.

5.1 Survival Analysis

While Yaraghi et al. (2015) have employed an Accelerated Failure Time (AFT) approach to survival analysis, we implement a Proportional Hazards (PH) model. The advantage of PH over AFT method is that it can analyze the effects of time-varying variables. Although interpretation of AFT models is easier, they cannot estimate the coefficients of variables that change over time. In our study, the odds of receiving referrals from HIE members changes over time and therefore in order to examine its effect properly, we need to implement PH models. We estimate the following equation using this approach:

$$ln\left(h_j(t)\right) = ln(h_0(t)) + \beta_3 R_{jt-1} + \boldsymbol{X}_j'\boldsymbol{\gamma}_3 \quad (3)$$

where $h_j(t)$ refers to the hazard function at time t for practice j. In the PH models, the hazard function is the probability that an individual will experience an event within a short time interval, given that the individual has survived up to the beginning of that interval. $h_0(t)$ is the baseline hazard function, and $R_{jt-1} = \frac{NR_{jt-1}^{HIE}}{NR_{jt-1}^{no-HIE}}$ is the odds of receiving referrals from HIE members for the focal practice j in the previous year, $t-1$ and X_j is to the vector of control variables for practice j. Control variables are defined as in table 2. In addition, we control for the variable S_{jt-1} which is the odds of sending referrals to HIE members for the focal practice j in year $t-1$.

To estimate equation 3, we use the PHREG procedure in SAS. To handle the time-varying covariates, we use the counting process method to construct the data. In this method, there may be more than one record per practice, where each record corresponding to an interval during which the time-varying covariate remains constant. For a detailed description of the procedure see (Powell & Bagnell, 2012).

Further, as a robustness test, we performed the survival analysis using the AFT model as shown in equation 4. We estimate this equation for years 2010, 2011, and 2012 separately, as follows. For each year t, we focus on the practices who have not yet adopted by the previous year $t-1$. These are the practices who have adopted in the period $[t, 2012]$ and the practices who remained non-members during the study. R_j denotes the odds of receiving patients from HIE members in the year prior to the analysis year (2010, 2011, or 2012). $TimeToAdopt_j$ is defined as the number of months since the beginning of the analysis year until practice *j* adopts HIE. We employ the LIFEREG procedure in SAS to estimate equation 4. Control variables are defined similar to equation 3.

$$ln\left(TimeToAdopt_j\right) = \beta_4 R_j + \boldsymbol{X}_{\boldsymbol{j}}' \boldsymbol{\gamma}_4 + \varepsilon_{4j} \; ; t \in \{2010,2011,2012\} \tag{4}$$

5.2 Network Analysis

Based on the discussion in Section 3, we posit that a HIE member, when faced with a comparable choice of options to refer a patient to, would prefer another HIE member over a non-member. Similarly, a physician who has more links with HIE members in the referral network is more likely to adopt HIE than another one with fewer connections to HIE members. Thus, having links with HIE members in the referral network and HIE adoption evolve together over time. The network modeling and analysis using SIENA is provided in Appendix 1. We summarize the modeling approach in the following discussion.

The network analysis using SIENA involves a stochastic actor-oriented modeling of the underlying network structure of the referral panel data. The network is stochastic because the referrals change over time; it is actor-oriented because the physicians are the actors who initiate the referrals. SIENA is designed to analyze longitudinal network data, i.e., two or more sets of observations over time where each set is referred to as a “wave” (Ripley et al., 2011). SIENA can also be used for modeling an actor’s behavior as a function of a network and actors’ covariates.

SIENA allows us to analyze the longitudinal data on social networks to model the *network* and *behavior* of actors jointly; this model is termed *co-evolution* (Ripley et al., 2011). The co-evolution model consists of a succession of mini-steps as the regular evolution model. At each mini-step, either the network or the behavior will be selected to change by an actor. Analyzing the co-evolution of referral network and HIE adoption allows us to simultaneously test the *social selection* in the referral network in which HIE members tend to select HIE members, and the *social influence* in which the non-members who are tied to HIE members are encouraged to adopt subsequently. This social selection and the social influence together determine the dynamic co-evolution of referral networks and HIE membership. In a social network both social selection and social influence are two dominant reasons which leads to similarity between tied actors (Snijders et al., 2010).

The co-evolution of referral networks and HIE adoption behavior is modeled as follows. At each mini-step of the co-evolution model, we consider two specific dependent variables: *referral network* and *HIE adoption.* First, using the rate function, the waiting time corresponding to each dependent variable is generated. Second, the dependent variable which has the lowest waiting time is selected. Next, an actor is randomly chosen to make the change on the selected dependent variable. Note that if the dependent variable is the referral network, then the chosen actor would make one of the following decisions: terminate a tie, create a tie, and remain in current state. If the dependent variable is HIE adoption, then the chosen actor would make one of the following decisions: if the actor has not yet adopted HIE, then the actor can either adopt HIE or not; if the actor has already adopted then the actor can only continue to be a HIE member. After the change, the corresponding dependent variable is updated and the procedure continues with the next mini-step.

6. Empirical findings

In this section, we first present the sample statistics and the results of the DID analysis. Second, we discuss the results on testing the DID assumptions. Third, we present the results of tests to rule out potential alternative effects. Finally, we discuss the findings of the analysis on the mutual effects between HIE adoption and referrals.

6.1 Sample Statistics

Table 3 presents a summary of referral data in Buffalo HRR over the period of study between 2009 and 2012 along with the number of practices and physicians affiliated with them that have adopted HIE over this period. There were 551 non-member practices with 1458 affiliated physicians at the beginning of the study period. Of this set, 205 practices and their 886 affiliated physicians adopted HIE during the period of our study, and the remaining 346 practices and their 572 affiliated physicians did not adopt. For the CEM analysis, the group of 205 practices is the treated group while the remaining practices constitute the candidates for the control group. The CEM analysis pruned these groups and yielded 101 practices within each group. Table 4 presents a comparison between treatment and control groups across the covariates before and after matching. As expected, these results show that after matching, the covariates are balanced between the treatment and control groups.

As discussed in section 5, the odds of receiving referrals from HIE members can influence the time to adopt in the future. This might create concerns regarding the validity of the DID analysis for testing H_3 and H_4. Specifically, for a proper inference from DID analysis, we need to assure that at each time *t* during the panel, HIE members and non-members of the matched sample are balanced regarding their odds of receiving patients from HIE members in year *t-1*. For this purpose, we tested the resultant matched sample for balance between the treatment and control groups regarding their odds as follows. First, for each year *t*, we compared the average of the odds variable for the group of practices who adopted in year *t+1* with the group of practices who have not yet adopted by *t+1*. This group of non-adopting practices includes those practices who have either adopted after *t+1* or not. Second, for each year *t*, we compared the average of the odds variable for the group of practices who have adopted in year *t+1*, with the group which has not adopted anytime in the panel of the study. The difference between HIE members and non-members in the average of the odds variable is not significant in any of these comparisons. Hence, HIE members and non-members in our matched sample are balanced regarding this variable too. The results are presented in the online supplement.

Table 3. Referral Data in Buffalo HRR

Year	No of Referrals	HIE adoption by Practices	HIE adoption by Physicians	Cumulative Number of HIE Adoptions by Practices	Cumulative Number of HIE Adoptions by Physicians
2009	11986	41	169	41	169
2010	11935	68	462	109	631
2011	12924	70	196	179	827
2012	13126	26	58	205	886

Total number of physicians in Buffalo HRR that are non-member by the beginning of 2009: 1458

Total number of physicians in Buffalo HRR that stay non-member by the end of 2012: 572 (1458-886=572)

Table 4. Comparison of Control and Treatment Group before and after CEM

	Before Matching			After Matching		
Variable	**Treatment**	**Control**	**P-value[1]**	**Treatment**	**Control**	**P-value***
NOP	10.528	3.692	<.0001	3.212	3.939	0.250
EHR	0.609	0.196	<.0001	0.435	0.435	1
PQRS	0.759	0.318	<.0001	0.654	0.654	1
ERX	0.634	0.156	<.0001	0.425	0.425	1
Urban	0.906	0.860	0.074	0.926	0.926	1
Degree Centrality	2.346	0.500	<.0001	0.614	0.416	0.150
Isomorphic Quotient	0.059	0.013	<.0001	0.018	0.020	0.837

[1]*: The level of significance for testing the hypothesis in which the difference between means of the two groups is zero.*

6.2 DID Analysis Results

In this section, we first provide the results on testing our main hypotheses (H_1-H_4). Table 5 presents the results from the Poisson model for testing H_1-H_4 (Eq. 1). The results show that HIE adoption significantly increases referrals sent to and received from other HIE members. This supports H_1 and H_3. However, the impact of HIE on referrals sent to and received from non-HIE members is insignificant. Thus, our findings do not support H_2 and H_4. The findings are consistent with the OLS model (Eq. 2) as in Table 6. The implications of the support for H_1 and H_3 and the potential reasons for the lack of support for H_2 and H_4 are discussed in detail in Section 8.

Table 5. Parameter Estimations (Standard Errors) Obtained from DID Model in Eq.1

Parameter	Referrals sent to HIE members	Referrals sent to Non-HIE members	Referrals received from HIE members	Referrals Received from Non-HIE members
HIE	0.37** (0.19)	-0.03 (0.07)	0.38** (0.17)	0.01 (0.07)
Time and Physician dummies	Yes	Yes	Yes	Yes
Full Log Likelihood	-39597.97	-30743.42	-38781.71	-28927.24

**p<0.05, *p<0.1, Columns 2-5 show the results on testing H_1-H_4 respectively. The Generalized Linear Model (GLM) is used to estimate the parameters of Eq.1. Standard errors in parentheses are clustered by practice. No of observations =1416 (No of Panels: 4, No of Physicians: 354) Among 354 physicians, 227 adopt HIE during the panel, and the rest remain non-member.

Table 6. Parameter Estimations (Standard Errors) Obtained from DID Model in Eq.2

Parameter	Referrals sent to HIE members	Referrals sent to Non-HIE members	Referrals received from HIE members	Referrals Received from Non-HIE members
HIE	0.59** (0.25)	0.11 (0.18)	0.49** (0.25)	0.13 (0.16)
Time and Physician dummies	Yes	Yes	Yes	Yes
R^2	0.90	0.93	0.92	0.93

**p<0.05, *p<0.1, Columns 2-5 show the results on testing H_1-H_4 respectively. The Ordinary Least Squares (OLS) is used to estimate the parameters of Eq.2. Standard errors in parentheses are clustered by practice. No of observations=1416 (No of Panels: 4, No of Physicians: 354) Among 354 physicians, 227 adopt HIE during the panel, and the rest remain non-member.

6.3 Testing for Common Trends Assumption

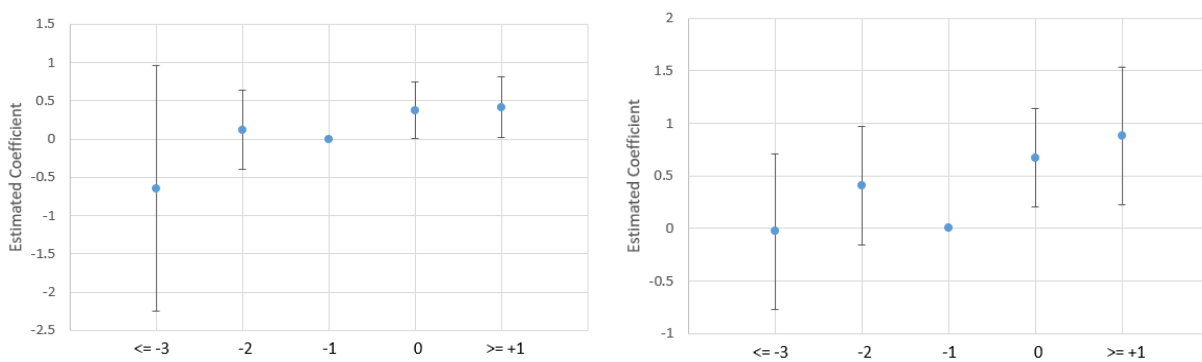
Using CEM in combination with DID analysis considerably reduces the bias from endogeneity. However, violations of the common trend assumption could still occur if there is any unobserved time-varying factor that impacts the control group and treatment group differently. To test this, and to evaluate the validity of our main empirical findings, we apply placebo tests and a leads and lags analysis.

Placebo Tests: To check the plausibility of the assumption that there are not any such confounders, we apply placebo tests using the approach implemented by (Hydari et al., 2019). In this approach, control group remains unchanged, the post-treatment data are removed, and the placebo treatments are created in the pre-treatment data. A failure to reject the null effect for the placebo treatment would provide support for the common trends assumption. Specifically, we apply the following two tests: In the first test, we remove the post adoption data, and assume that HIE adoption happens one year before the actual date of adoption. In the second test, we assume that HIE adoption happens two years before the actual date of adoption. For each test, we run the proposed specifications in equations 1 and 2 using the new dataset. If the results do not show any significant impact of placebo treatment, then the common trends assumption is supported. The results are presented in the online supplement. The results show no significant impact of placebo treatment on outcome variables.

To further check whether members and non-members have similar trends in the pre-adoption period and ensure that we are not capturing a general time trend, we conduct an alternate test presented in (Chang et al., 2019) . In this test, the control group remains unchanged, the post-treatment data are removed, and the placebo treatments are created in the pre-treatment data. Then, the placebo treatment variable H_{ij} is defined as 1 for any physician *i* belonging to practice *j* who is about to adopt in the period of our study, and 0 otherwise. The count variable $Time_t$ is equal to 1 to 4 corresponding to each year of the panel. If the pre-treatment parallel trend assumption holds, the estimated coefficient of the variable $H_{ij} \times Time_t$ in equation 5 should be insignificant. We note that the rest of the variables in equation 5 are as defined in equation 1. The results are presented in the online supplement. We have not observed any significant effect of the variable $H_{ij} \times Time_t$ in either of our outcomes.

$$ln(y_{ijt}) = \alpha_{5t} + \gamma_{5i} + \beta_5 H_{ij} \times Time_t + \delta_5 Time_t + \rho_5 H_{ij} + ln(N_{ijt}) \quad (5)$$

Leads and Lags analysis: Following the literature (Autor, 2003; Sun et al., 2020), we checked whether there is any differential pre-trend in the outcomes of interest between HIE adopters and non-adopters using the leads and lags analysis. We created five dummy indicator variables as follows: one for 3 years before HIE adoption and backward (denoted as $HIE_{t-3\ \text{backward}}$), one for 2 year before adoption (HIE_{t-2}), one for 1 year before adoption (HIE_{t-1}), one for the year of adoption (HIE_{t0}), and one for 1 year after adoption and forward ($HIE_{t+1\ forward}$). The indicators are equal to 1 only in their corresponding year(s). In the other words, for physician *i* in year *t*, only one of these indicators is equal to 1. We consider the indicator HIE_{t-1} as the baseline (i.e. omitted variable) in the regression. We then estimate equations 1 and 2 (Poisson and OLS models) by replacing the variable *HIE* with these indicators. Figures 2 and 3 plot the estimated coefficients of the indicators when testing supported hypotheses. The x-axis labels correspond to each indicator, and show the relative time to HIE adoption. For example, -2 shows two years before adoption. Figure 2 corresponds to the referrals sent to HIE members (H_1) and Figure 3 to the referrals received from HIE members (H_3). The coefficient estimates for the indicator $HIE_{t\text{-}3\ \text{backward}}$ and $HIE_{t\text{-}2}$ are insignificant when modeling our outcomes of interest, and HIE adopters pick up the effect since the adoption year. Thus, we find no evidence of pre-trend difference that might have impacted our findings.

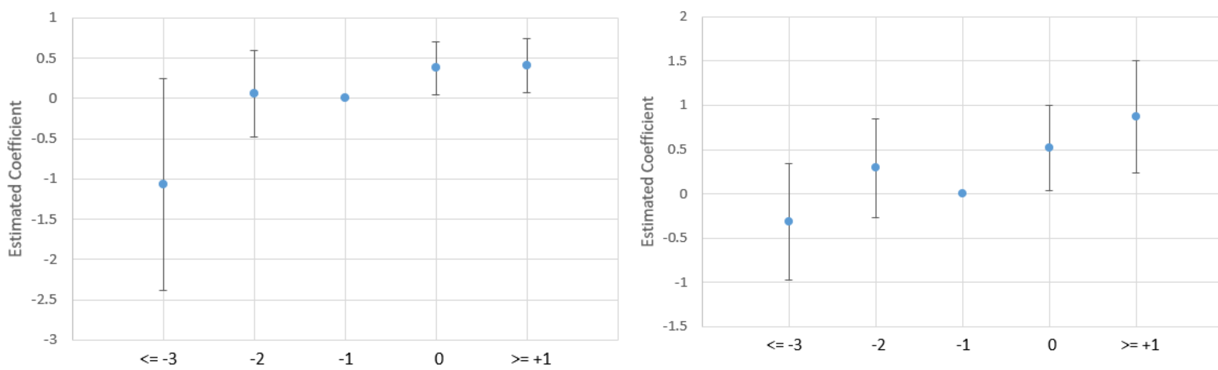


(a) Poisson Model (Eq.1) (b) OLS Model (Eq.2)

Figure 2. Leads and Lags Analysis on Referrals Sent to HIE Members (Bars show 95% confidence intervals).

The Poisson model indicates that the effect of HIE adoption tends to level off after two years, and the OLS model shows that the effect is slightly increasing. A potential explanation for the slow pace at which HIE is impacting referrals is as follows. Similar to any information technology product, the HIE users would begin to expect enhancements to HIE as time goes by. As a result, the impact of HIE on referral decisions by its members could level off over time, unless the enhancements are periodically delivered to the market. In this regard, we note that there were no product versioning or enhancements during the period of our study. We further note that with the growth in the population of HIE members, the referrals sent to/received from HIE members would increase anyway, and hence upon adoption and over time, the specific effect of HIE on referral decisions could level off. Since our panel is short, we believe that any trend analysis may not be able to provide strong insights on the effect of HIE adoption over time. Deeper theoretical and empirical investigation on the trend of HIE impact on referrals are recommended for future research.

The leads and lags analysis on the unsupported hypotheses (H_2 and H_4) are presented in the online supplement. We did not see any placebo effect or an effect of adoption over time.



(a) Poisson Model (Eq.1) (b) OLS Model (Eq.2)

Figure 3. Leads and Lags Analysis on Referrals Received from HIE Members (Bars show 95% confidence intervals).

6.4 Probing the Outlier Effects

HIE adoption happens at different points of time in the period of our study. One might be concerned on the heterogeneity of the HIE effects over time. The period of our study is not long enough to allow us to study the heterogeneity of the HIE effect over time. However, we conduct multiple tests to assure that the potential heterogeneity of the HIE effect has not created a bias in the significance of the DID estimator obtained from our proposed specification.

Goodman-Bacon Weighted Average Analysis: The DID estimator obtained from any two-way fixed effects model in which treatment happens at different points of time is a weighted average of all possible two-by-two DID estimators that can be obtained from the panel data set. Each two-by-two DID estimator is obtained by comparing two groups where one group acts as the *treatment* and the other as *the control* (Goodman-Bacon, 2018). Some of these comparisons use units that are treated at a particular time as the treatment group and the untreated units as the control group. Other comparisons use units that are treated at two different times, first using the group that is treated *later as a control before* its treatment begins, and next, using the group that is treated *earlier as a control after* its treatment begins. As discussed by Goodman-Bacon (2018), if the impact of treatment effect varies over time, then the DID estimator obtained from the proposed DID specification can be biased. The potential source of bias could come from the estimators in which a group of early treated units act as control. We employ the *bacondecomp library* in R to derive the underlying DID estimators and their corresponding weights. A summary of this analysis for the outcomes of interest in the supported hypotheses (H_1 and H_3) is presented in table 7. The potential heterogeneity of the HIE effect over time will not create a significant bias in estimators obtained from the proposed DID specification due to the following reasons. First, and most importantly, our panel is short, and thus the periods over which that treated units act as controls is short. Second, the weights corresponding to comparisons in which treated groups act as controls are significantly lower than the weight of the comparison in which they act as treatment. Third, as table 7 shows, the average DID estimators are in the same direction and fairly close to each other. Specifically, the overall DID estimators for each outcome of interest obtained from the proposed DID specification (see table 5) are close to the DID estimator obtained from the comparison in which a treated group is comparted with the untreated group. The test results on the unsupported hypotheses (H_2 and H_4) are presented in the online supplement.

Table 7. Goodman-Bacon Weighted Average Analysis on the Outcomes

Type of comparison (Treatment Vs. Control)	**Weight**	**Average of DID estimate (Referrals Sent to HIE Members)**	**Average of DID estimate (Referrals Received from HIE Members)**
Earlier Vs. Later Treated	0.04	0.6	0.48
Later Vs. Always Treated	0.28	0.45	0.51
Later Vs. Earlier Treated	0.07	0.85	0.63
Treated Vs. Untreated	0.61	0.55	0.53

Calloway and Sant'Anna DID Framework: For a deeper test of validity of our proposed two-way fixed effects (TWFE) model, we further analyzed our data using the DID estimators developed by Callaway and Sant'Anna (2020). While the Goodman-Bacon analysis provided a validity check on our proposed DID effect, the Callaway and Sant'Anna framework provides in addition, alternate DID estimates that avoid potential issues in the interpretation of the TWFE model by allowing for treatment effect heterogeneity.

Callaway and Sant'Anna's DID framework is mainly based on the disaggregated causal parameter called the group-time average treatment effect, i.e., the average treatment effect for a specific group in a specific time period, where a "group" is defined by the time period when its units are first treated. In traditional DID models (with two groups and two periods) these effects reduce to the average effect of treatment on the treated (ATT) which is typically the parameter of interest. In the Callaway and Sant'Anna framework, these effects are then used as building blocks for more aggregated treatment effect parameters which are developed to highlight treatment effect heterogeneity as well as to summarize the overall effect of participating in the treatment. Their aggregation schema immediately avoids the negative weights issue that TWFE models can potentially suffer from. In particular, their framework provides a single overall treatment effect parameter with similarities to the ATT in the traditional DID model, as well as partial aggregations that highlight heterogeneity of the effects. More specifically, they first develop a simple-aggregated effect, which is just an average of all the group-time average treatment effects with weights proportional to the group size. This simple combination immediately rules out potential issues due to negative weights in TWFE models. Hence, the simple-aggregated effect by itself provides effective robustness check to our DID effects. Callaway and Sant'Anna further provide better alternatives such as DID dynamic effects, since the simple aggregation tends to overweight the effect of early treated groups simply because we observe more of them during post-treatment periods. The dynamic effects are averages of ATTs at different lengths of exposure to the treatment. They estimate an overall DID parameter as an average of the dynamic effects, which we refer to as the dynamic-aggregated effect. The group-aggregated effect is defined analogously.

We employ the *did library* in R developed for the Callaway and Sant'Anna framework to analyze the DID effects. The results for testing the supported hypotheses (H_1 and H_3) are presented in Tables 8 and 9. The *did library* by default uses the "never-treated" group as the control group. We further analyzed the effects by using the "not-yet-treated" sample. The results of the analyses are consistent. The "not-yet-treated" sample includes the never-treated units as well as those that have not yet been treated at a particular point in time. In all models, the Wald pre-test confirms the parallel trends assumption.

The simple-aggregated effects presented in tables 8 and 9 are significant and fairly consistent with our proposed DID effects. In our context, the simple-aggregated effects themselves sufficiently validate our findings. This is because our panel is short, and the simple aggregation does not suffer from overweighting the effect of early treated groups.

In tables 8 and 9, "event time" shows the relative time to HIE adoption. For example, -2 shows two years before HIE adoption, and 0 shows the year of adoption. The dynamic effects in tables 8 and 9 show that we do not observe any pre-treatment effects on the outcomes of our interest. We note that in the Callaway and Sant'Anna framework, the group that adopts in the first year of the panel is excluded from the analysis. The results on the dynamic effects yield further test and validation of the common trends assumption. The dynamic effects show that the physicians pick up the effect in the year of adoption. The observed trend of the HIE impact is largely consistent with the leads and lags analysis in section 6.3. However, we note as the panel is short, the insights on the trend of the HIE impact is limited. For example, in the Callaway and Sant'Anna DID framework the impact of adoption after 2 years is obtained based on only the group who adopted HIE in year 2010. Hence, this effect does not provide strong insight on the overall effect of adoption after 2 years. Finally, the dynamic-aggregated and group-aggregated effects are significant when modeling the outcomes of our interest providing additional support for our main findings.

Table 8. Callaway and Sant'Anna DID effects for the HIE impact on referrals sent to HIE members (H_1)

	Control group: Never-treated sample		Control group: Not-yet-treated sample	
Simple-aggregated Effect	0.54^{**} (0.23)		0.52^{**} (0.22)	
Dynamic Effects (Event Study)	Event time	ATT (SE)	Event time	ATT (SE)
	-2	-0.16 (0.31)	-2	-0.03 (0.28)
	-1	-0.11 (0.26)	-1	-0.08 (0.27)
	0	0.43^{**} (0.17)	0	0.42^{**} (0.17)
	1	0.81^{**} (0.26)	1	0.77^{**} (0.25)
	2	0.22 (0.44)	2	0.22 (0.42)
Dynamic-aggregated Effect	0.48^{**} (0.24)		0.47^{**} (0.23)	
Group-aggregated Effect	0.55^{**} (0.22)		0.52^{**} (0.20)	

$^{**}p<0.05$, $^{*}p<0.1$

Table 9. Callaway and Sant'Anna DID effects for the HIE impact on referrals received from HIE members (H_3)

	Control group: Never-treated sample		Control group: Not-yet-treated sample	
Simple-aggregated Effect	0.48^{**} (0.21)		0.45^{**} (0.21)	
Dynamic Effects (Event Study)	Event time	ATT (SE)	Event time	ATT (SE)
	-2	-0.27 (0.28)	-2	-0.11 (0.28)
	-1	-0.01 (0.29)	-1	0.03 (0.27)
	0	0.31^{*} (0.16)	0	0.28 (0.16)
	1	0.71^{**} (0.26)	1	0.67^{**} (0.25)
	2	0.46 (0.44)	2	0.46 (0.45)
Dynamic-aggregated Effect	0.49^{**} (0.24)		0.47^{**} (0.23)	
Group-aggregated Effect	0.44^{**} (0.21)		0.41^{**} (0.20)	

$^{**}p<0.05$, $^{*}p<0.1$

The Callaway and Sant'Anna DID results on the HIE impact on the referrals sent to/received from non-HIE members (H_2 and H_4) are presented in the online supplement. The results do not show significant HIE effects which is consistent with our main findings from the TWFE models.

DID Analysis on the Treated Sample: According to (Goodman-Bacon, 2018), when the treatment effect varies over time, the DID estimators using only the treated sample is very different from the DID estimator of the sample including the untreated units. Hence, we ran the DID specification in equation 1 only on the treated sample for testing H_1 and H_3. The results with the Poisson model for the supported hypotheses (H_1 and H_3) are reported in table 10. The rest of the analyses are reported in the online supplement. The DID estimator in this analysis is fairly consistent with the DID estimator obtained from the whole matched sample. We thus conclude that the heterogeneity of the effects is not a concern in our case.

Table 10**.** Parameter Estimations (Standard Errors) Obtained from DID Model in Eq.1 with only the Treated Sample

Parameter	**Referrals sent to HIE members**	**Referrals received from HIE members**
HIE	0.47 (0.22) **	0.49 (0.22) **
Time and Physician dummies	Yes	Yes
Full Log Likelihood	-29109.87	-28236.48

$^{**}p<0.05$, $^{*}p<0.1$, Columns 2-3 show the results on testing H_1 and H_3 using only the treated sample respectively. The Generalized Linear Model (GLM) is used to estimate the parameters of Eq.1. Standard errors in parentheses are clustered by practice. No of observations =908 (No of Panels:4, No of Physicians: 227)

Leads and Lags Analysis on the Treated Sample: We conducted a leads and lags analysis as described in Section 6.3 using only the treated sample. The plots are presented in the online supplement. The results are fairly consistent with the analysis using the whole matched sample. The coefficient estimates for the indicator $HIE_{t-3\ \text{backward}}$ and HIE_{t-2} are insignificant when modeling referrals sent to HIE members (H_1), and HIE adopters pick up the effect since the adoption year. However, a significant impact on the referrals received from HIE members is observed in the Poisson model (H_3). This could presumably imply that physicians who are not HIE members but are about to adopt HIE in the next year, have received more referrals from HIE members compared to others who will adopt after three years. We believe that this is not a concern since the OLS model does not confirm this and the leads and lags analysis on the whole sample does not imply such observation. The results regarding the unsupported hypotheses (H_2 and H_4) do not show any concern as well.

6.5 Exploratory Analysis of Observed Networks

In the following, we first study the potential effects of observed networks among physicians on the HIE impact in order to evaluate the validity of our findings. Next, we discuss the insights that can be derived from this analysis.

Effects of Observed Networks: We note that in a HRR, there could be multiple Integrated Delivery systems (IDS). An IDS consists of a few providers that provide a coordinated continuum of services to a defined population. The Pan American Health Organization (2008) defines IDS as groupings of organizations that provide similar levels of care under one umbrella. There are two IDS networks in the Buffalo HRR, both comprising of HIE member and non-members. The physicians may affiliate with one or both of the networks. 18.23% of physicians in Buffalo HRR belong to IDS 1, 18.82% belong to IDS 2, and 26.95% belong to both. Since physicians may prefer to refer their patients to those in the same IDS, there could be an IDS effect on the impact of HIE on referrals. We thus checked for the robustness of the results by conducting separate analyses for the sample of physicians who are members of an IDS, and the sample of the physicians who are not member in any IDS. The results with equation 1 (Poisson model) are reported in tables 11 and 12 respectively. The results using OLS model are presented in the online supplement. The impact of HIE on the referrals sent to and received from HIE members is significant in both samples. Thus, the analysis of the observed networks confirms the robustness of the findings on H_1 and H_3. Further, similar to our main results, H_2 and H_4 are not supported in this analysis.

Insights from the Analysis: Integration of healthcare services has been shown to yield the following benefits: increased collaboration and coordination among the providers, minimization of redundancies and waste leading to better cost containment, improved partnerships with payers, improved patient-centered communication and overall community health, improved pharmaceutical management and patient safety (Al-Saddique, 2018). Therefore, such integrated services lead to reduced costs and enhanced quality in the continuum of care (Hwang et al., 2013). Consequently, we believe that the referrals within an IDS would involve lower transaction costs than those outside of an IDS. The results shown in Tables 11 and 12 reveal that the HIE impact on referrals sent to/received from HIE members is stronger for physicians in the non-IDS sample. The lower HIE effect observed in the IDS sample could presumably be explained by the lower transaction costs due to the IDS services. As per the proposed mechanism, physicians would consider referrals to HIE members because of its ability to reduce the associated transaction costs and potential frictions. Hence, the physicians belonging to an IDS should be less motivated to consider the HIE channel for referrals than those who are outside an IDS. For IDS physicians, considering HIE as a factor in their referral decision making might not be as important as the factor of being in the same network. Further, an IDS promotes collaboration among its members, and collaborations require teamwork. Teamwork, over a sustained period, leads to deeper relationships among the physicians. As a result, besides the transaction cost advantage, these built-in relationships could facilitate referrals within an IDS and thus could contribute to lowering the impact of HIE among physicians belonging to an IDS. A deeper theoretical and empirical investigation would be needed to distinguish between the cost advantage and the built-in relationships on the referrals.

Table 11**.** Parameter Estimations (Standard Errors) Obtained from DID Model in Eq.1 Using IDS Members

Parameter	**Referrals sent to HIE members**	**Referrals sent to Non-HIE members**	**Referrals received from HIE members**	**Referrals Received from Non-HIE members**
HIE	0.33 (0.2) *	-0.06 (0.09)	0.34 (0.18) *	-0.02 (0.07)
Time and Physician dummies	Yes	Yes	Yes	Yes
Full log Likelihood	-33753.64	-24857.06	-33241.69	-22616.87

**p<0.05, *p<0.1, Columns 2-5 show the results on testing H_1-H_4 respectively on the sample of IDS members. The Generalized Linear Model (GLM) is used to estimate the parameters of Eq.1. Standard errors in parentheses are clustered by practice. No of observations =1052 (No of Panels: 4, No of Physicians: 263) Among 263 physicians, 178 adopt HIE during the panel, and the rest remain non-member.

Table 12. Parameter Estimations (Standard Errors) Obtained from DID Model in Eq.1 Using Non-IDS Members[5]

[5] The findings of tables 11 and 12 are largely consistent with the corresponding results obtained with the Eq. 2 (OLS model) presented in the online supplement.

Parameter	Referrals sent to HIE members	Referrals sent to Non-HIE members	Referrals received from HIE members	Referrals Received from Non-HIE members
HIE	0.85 (0.46) *	0.04 (0.09)	1.04 (0.4) **	0.09 (0.09)
Time and Physician dummies	Yes	Yes	Yes	Yes
Full log Likelihood	-4839.06	-5092.79	-4276.71	-4840.10

**p<0.05, *p<0.1, Columns 2-5 show the results on testing H_1-H_4 respectively on the sample of non-IDS members. The Generalized Linear Model (GLM) is used to estimate the parameters of Eq.1. Standard errors in parentheses are clustered by practice. No of observations =364 (No of Panels: 4, No of Physicians: 91) Among 91 physicians, 49 adopt HIE during the panel, and the rest remain non-member.

6.6 Test for Unobserved Networks

Besides the potential effects of observed networks, one might be concerned that there may be some unobserved networks, where participation in them could affect both HIE adoption and referral decisions by practices. For example, if two practices get acquired by a large hospital and become a part of its larger network, then they will follow the policy of the hospital on both HIE adoption and referral management. If such networks exist, ignoring them could lead to potential bias in our estimates. In the following, we propose a heuristic approach to identify any unobserved networks in our data.

The challenge for us was the fact that such potential networks are unknown to us, and unlike other clusters such as IDS or HRR or insurance networks, there are no formal definitions for such networks to help us identify them. Although the networks *themselves* are unknown to us, their *effects* should be observed in our data. Our contention is that if such networks exist, then their effect should be observed on both the HIE adoption and referral decisions among their members. For discovering the possible existence of these networks, we devised the following strategy.

For every pair of practices i and j, let $T_{ij} > 0$ denote the gap between their dates of their HIE adoption in months. Let p_{ij} denote the proportion of the total referrals from i that are sent to j. Define these quantities for every pair i and j. Let $P_{ij} = Min\{p_{ij}, p_{ji}\}$. The criterion T_{ij} is a measure of closeness between a pair of practices with respect to their dates of adoption; the criterion P_{ij} is a measure of closeness between a pair of practices in terms of their mutual referrals to each other. Smaller the T_{ij} and larger the P_{ij}, then clearly the closer the two practices are. Using threshold values D and R for T_{ij} and $P_{ij,}$ respectively, we group all practices where $T_{ij} < D$ and $P_{ij} > R$ together and assume that they are the members of the same unobserved network. This will construct network of practices that have adopted HIE at the same time and refer a significant portion of their patients to each other.

Note that the number of practices in a network is monotonically non-decreasing as D increases and R decreases. Using this principle and from a meaningful and practical viewpoint, we formed networks at highly relaxed thresholds $D = 3$ months and $R = 50\%$. That is, we assumed that practices that have adopted within 3 months of each other and refer at least 50% of their patients to each other, are members of the same network. Even at these levels, we could not find any non-empty network of practices. This implies there is no significant inter-practice network effect which impacts both HIE adoption decisions and referrals.

Our above analysis shows there is no concern regarding the potential impact of confounding factors due to unobserved networks on our outcomes of interest. Furthermore, since we use only Medicare data, any potential effects due to insurance networks do not exist in this study either. HIE is a precursor technology to that of referral management systems, and there were no referral management systems in existence during the period and in the region of our study.

6.7 Mutual Effects Analysis

Survival Analysis Results: The results of PH model (equation 3) and AFT model (equation 4) are presented in the online supplement. The significantly positive estimated parameter R_{t-1} in PH model indicates that an increase in the odds of receiving referrals from HIE members leads to an increase in the hazard of HIE adoption. The AFT model is separately run for each of the years 2010, 2011, and 2012. The significantly negative coefficients for R in the AFT model indicate that it takes less time to adopt HIE for practices with higher odds of receiving referrals from HIE members. Our findings are consistent with (Yaraghi et al., 2014a).

Network Analysis Results: The network analysis results are reported in detail in the Appendix 1. These results support our above findings with regard to the mutual impacts between HIE membership and referral choices, and thus, provide a validation of our proposed hypotheses. This model expresses the inter-dependent evolution of the adoption and referral decisions by showing how they sequentially develop by mutually taking each other into account. In fact, we have shown that, there are pathways of sequential decisions made by physicians with regards to HIE adoption and referral choices that could explain the diffusion of HIE membership and changes in the referral patterns occurring in mutual interdependence over time.

7. An Exploratory Field Study

Motivation: The proposed mechanism explains why a HIE member would prefer to refer patients to another member. The logic underlying this mechanism is based on the three service attributes of HIE in information sharing: timeliness, recentness and accuracy, and completeness, altogether leading to lowering the transaction costs of referrals. According to this logic, HIE could potentially dominate other channels of information sharing in terms of these attributes and hence, would lead to its preference by its members. Our hypotheses were derived from this logic and were subsequently tested empirically using panel data. These empirical findings shed considerable light on the hypotheses and hence, on the proposed mechanism. As an additional and direct exploration to validate the proposed logic, we conducted a field study that involved in-depth interviews with HIE members. More specifically, this direct exploration entailed two goals: to *confirm* the proposed logic and to *discover* potential reasons for the findings that are contrary to our expectations from the empirical study.

Data Collection: To identify our interviewees, we adopted the extreme case selection approach (Gerring, 2017). This was based on the assumption that early adopters of HIE and those who use it more than others, would have more insights on the impact of HIE on their workflows. We consulted with HEALTHeLINK management team and identified eight members for the study. All interviews were conducted over Zoom, and were recorded and transcribed. The average length of an interview was 41.3 minutes in the range between 17 and 61 minutes. Upon transcription, the average length of interviews was 8658 words in the range of 3572 to 13756 words. The interviews consisted of open-ended questions. Each interview started with simple questions about the role of interviewees in their organizations, characteristics of their medical practices, and their opinions about HIE in general. We continued by asking them to describe how they used HIE in their workflows when they see patients. We asked the interviewees to walk us through a referral case in which they send to or receive from a HIE member. To compare and contrast, we asked them to walk us through a referral case with a non-member. We then finished the interview by asking questions focused on the factors that physicians consider in referrals. The interview protocol is provided in the online supplement.

Data Analysis: The interview scripts were analyzed using content analysis, which is a well-established methodology for analyzing qualitative data. Content analysis starts with transcribed interviews. The text is then transformed into organized and summarized key findings. We followed the ontological framework provided in (Erlingsson & Brysiewicz, 2017) for this analysis. According to this framework, the *meaning units* of the raw text are extracted first. Next, the meaning units are progressively abstracted into *condensed meaning units, codes*, *categories* and *themes,* in increasing levels of abstraction. We followed the four-stage process of data analysis in Bengtsson (2016) for building this ontology. The ontology was built manually and independently by each author. A consensus was reached in a progressive manner through discussion and deliberation. Six main themes emerged from this analysis. A summary of the findings is presented in Appendix 2. These findings are hierarchically organized and each path from a code to a theme presents a wholly self-contained and complete abstraction of a concept.

Conclusions*:* Themes T1 and T3 specifically address the primary purpose of this study. T1 shows that HIE members view HIE as better than other channels for information sharing in referrals due its ease, speed of access, completeness and recentness of data. This finding is consistent with our proposed mechanism and confirms its underlying logic. We also note that as presented in the codes, HIE members mentioned the potential improvements in patient satisfaction with the quality of their services that resulted from using

HIE. This is consistent with the expectations on HIE platforms in the literature. Some quotes from the interview scripts that lead to theme T1:

One HIE member highlighted how HIE enables timely access to medical records:

> *"Before HIE, once we received a fax or a phone call from a referring physician, that fax or the message from the phone call would go in a paper basket. The staff would come in and find that paper basket and then pick up the phone and call the hospital and then the hospital would fax over some more information and we would pay clip it all this information together on paper and give it to the doctor. The doctor would say "I need to see this person in one week or one month or schedule a test" and then a whole pack of paper would go back to somebody else who would make a phone call to the patient and then fax the whole big thing back to the primary care office and tell them "we are going to see your patient next month". That whole process took us 30 days, with HIE, we do the same process within five days!"*

One HIE member discussed how HIE enables comprehensive access to medical records:

> *"There is a lot of stigma around medical conditions of our patients, so in many cases, patient does not disclose that she was at the hospital before or had specific medications. She may even say, "oh! that was my twin sister". In many other instances, patients do not remember exactly what happened at their previous encounter with other physicians. Without HIE, we will not be able to get the full picture. "*

One HIE member described how ADT notifications enables their gynecology practice to proactively develop a care plan for their patients:

> *"Before [a major hospital in the area] adopted HIE, if one of our patients felt contractions and was rushed to the ED during the weekend, and called us on Monday to notify us, they did not know exactly what was done for them at the hospital, and the hospital would not disclose the records to us, unless we had the patient come to office and sign a consent to release records, we then had to fax it to the hospital to receive the records and know what exactly happened. This whole process could take days, with HIE, we get notified immediately and can plan for patient's follow-up visits even before they call us."*

Finally, theme T3 reveals that there are still some factors other than HIE that physicians may consider in making referral choices. These factors include relationships among physicians, clinical appropriateness of potential referral choices for patients, patients' own preferences for the referred physicians, and limited set of suitable physicians to refer. This finding sheds light on the potential reasons for observing that HIE adoption by a physician does not lead to a significant decrease in the number of referrals to non-HIE members.

8. Discussion and Conclusion

Efforts for promoting HIE have been undertaken nationwide since the enactment of the Health Information Technology for Economic and Clinical Health Act. However, despite investments at the federal, state, and local levels, the physicians' engagement with HIE has been somewhat modest. The biggest challenges include financial sustainability, interoperability, and competition in healthcare markets. The last challenge, competition, is a very critical problem that relates to the focus of this research, referrals. We are yet to understand how HIE affects referral patterns, and hence analyzing and establishing this link is practically a very important problem. In this paper, we first develop a mechanism to explain a set of proposed effects of HIE on referrals. Next we empirically test for the existence of these effects. Finally we conduct an exploratory field study to gain additional insights on the proposed mechanism. In the following, we summarize the findings of this research, present the implications of this work to research and practice, and discuss directions for future research.

Summary of Findings: Hypotheses H_1 and H_3 are supported. These imply that HIE adoption increases the referrals sent to/received from HIE members. Further, our exploratory analysis on the observed networks reveal that the HIE impact on referrals sent to/received from HIE members is stronger for physicians who do not belong to any IDS. As referrals within an IDS would involve lower transaction costs than those outside of an IDS, the lower HIE effect observed in the IDS sample could provide additional support to our proposed logic underlying the impact of HIE on referrals. Furthermore, the exploratory field study has revealed that HIE members perceive HIE to be better than other channels of information sharing due its ease, speed of access, completeness and recentness of data, and thus confirming the proposed mechanism.

Hypotheses H_2 and H_4 are not supported. The lack of support of H_2 indicates that the level of referrals made by HIE-members to non-members continues on the same trend as it was before their HIE adoption. The potential reason for this is as follows. The patient population in a HRR fluctuates over time, and depending on the population growth rates of the underlying communities, typically exhibit specific trends. Our referral data shows that there has been a gradually increasing trend in the total number of patients in the Buffalo

HRR over the period of this study[6]. So, when physicians, upon HIE adoption, increase their referrals to other HIE members (H_1), they need not necessarily decrease their referrals to non-members, and hence, could continue to maintain their prior trend. The lack of support for H_4 indicates that HIE members continue to receive referrals from non-members on the same trend as it was before their HIE adoption. The potential reason for this is as follows. Physicians would accommodate incoming referrals as long as the services can be rendered within the limits of their referral-handling capacities. Our referral data shows that the average referral handling capacity of a physician exceeds the average number of referrals received by the physician in each year during the period of our study[7]. These values are presented in the online supplement. This indicates that physicians did not operate in their full capacities during our study period. Therefore, when physicians, upon adoption, receive more referrals from HIE members (H_3), they need not decline referrals coming from non-members, and hence, continue to maintain their prior trend. Finally, one might argue that if physicians have sufficient referral handling capacities then why HIE members do not send much more of their patients to other HIE members to the extent that we will see a greater impact of HIE, leading to even supporting H_2. In other words, one might ask why referrals to non-members are not reduced if there is sufficient capacity available with HIE members. In this regard, we would like to note that referral relationships among physicians that may be built over time tend to sustain longer before referral behaviors change. The field study revealed that there are some important factors pertaining to relationships among physicians that make physicians to continue to refer to certain other physicians. Two of the respondents in our field study provided the following insight on the importance of the relationships in referrals:

> *"Over time, I have gained a lot of knowledge about most other specialists in the area, so when it comes to referring one of my patients, I will refer to the one whom I trust would be able to provide the best services, regardless of their HIE membership."*
> *"....and these doctors have been here for years. These doctors go to parties together ... you know, country clubs, these doctors are friends. I mean, that's how small this community is"*

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[6] Similar trends have been observed in number of patients in the respective sub-populations of members and non-members. The fluctuations and trends in the population of patients studied in this research thus will not be of concern regarding the estimation of the HIE impact on the referrals sent to/received from HIE members. We further have assured that there was no significant difference in total number of patients among members and non-members of our matched sample in different years. Finally, we note that we did not find any significant effect of HIE adoption on total number of referrals (sent to/received from).

[7] We used the maximum number of referrals handled by a physician over the study period as a measure of the referral handling capacity of the physician. This maximum is a lower bound on the physician's referral-handling capacity.

However, such existing relationships may not continue to influence the referral decisions over longer periods of time as HIE matures; it will be interesting to investigate such trends in future research.

Finally, since our panel is short, interpretations of the HIE impact over time obtained from the trend analyses could be limited. We believe that further empirical investigation is required to explore trends that may occur beyond the panel studied. This is recommended for future research.

A Report Card on HIE: The support of hypotheses H_1 and H_3 and the lack of support for H_2 and H_4 together yield a mixed report card for HIE. While HIE enabled its adopters to shift their existing referral practices more towards referrals within the adopter segment, it did not significantly tilt their referrals away from the non-adopter segment during the period of our study. In other words, upon HIE adoption, the cannibalization of referrals going to non-adopters by referrals going to adopters did not fully occur. This implies that HIE did not enjoy a dramatic market externality on referrals during its early stages which coincided with the period of this study. This can be explained as follows. The concept of HIE was born out of a federal mandate, and accordingly, should be differentiated from other innovations that could experience rapid network externalities upon their arrival in the market. Besides this, the nascency of HIE, the reliance on federal support during the initial periods, and its relatively complex technology development cycle would potentially account for this mixed report. Further, we also note that in general, understanding and attaining a level of comfort with an information technology by its users would be important considerations in the eventual use of the technology in their workflows, especially when the technology tends to be disruptive. These open up several imperatives and opportunities for HIE developers.

Managerial Implications: The current research yields several managerial implications to both medical practices and HIE platform businesses. Prior research on HIE has shown that HIE could yield significant benefits to patients and insurance companies by improving the quality and reducing the cost of healthcare. However, the extant literature does not address the benefits from a HIE to its participating physicians. Our research focuses on this missing link and shows how the value proposition of a HIE platform is being realized by its participating physicians. HIE has segmented the physician community into HIE *haves* and *have-nots.* Our research shows that this segmentation could lead to a balkanization of the physician community where the haves tend to benefit at the cost of the have-nots in terms of referrals. The theme of balkanization of societies by information technologies has been well studied in the IS literature since the original work by Van Alstyne and Brynjolfsson (1996) . Our research shows that HIE has the potential to gradually result in patient leakage from the have-nots to haves, while at the same time, increasingly shield the haves against leakage from their segment. In other words, while HIE non-members could continue to experience leakage over time, the members could be sealing off the leakage from their segment. This indicates that a potential for balkanization exists. To deeply explore this phenomenon, an analysis using a larger panel of data is recommended for future research. Our research finding would inform the non-members of this value of HIE and consider becoming members. This phenomenon —in which HIE haves could benefit at the cost of HIE have-nots— is in contrast to the positive spillover phenomenon observed in the study of Atasoy et al. (2018) where the have-nots of a health IT benefit from the haves. They showed that the operational costs of the have-nots decrease because of the haves, whereas we show that patient leakage is occurring from the have-nots to the haves.

The report card from this study would inform the HIE platform developers on their marketing strategies and how to position their services in the physician market segments. The providers should adopt a parallel strategy of creating greater awareness of the advantages of HIE in the member segment in order to increase their level of HIE usage in referrals, and simultaneously creating an awareness on the threat of potential patient leakage in the non-member segment that could occur as a result of increased HIE-based referral activity in the member segment. The marketing strategy in the member segment requires innovations in the product offering, and the strategy in the non-member segment requires persuasive marketing communication. Furthermore, participation of physicians in an IDS should be considered in the marketing strategy. The higher impact of HIE on referrals initiated by non-IDS physicians compared to the IDS physicians shows that the market segment of non-IDS physicians should be a prime target for HIE platform developers in their marketing efforts. For physicians who are not yet members of HIE, the transaction cost advantage of HIE in referrals will be a sound marketing message; this message will be more convincing for physicians who do not belong to any IDS. However, for IDS physicians who are non-members of HIE, this message may not be sufficient and they will need additional persuasion to join the HIE. The strategy for promoting HIE usage among its members would also fork along the lines of whether the physicians belong to an IDS or not. The HIE developers should concentrate on product innovations and versioning to continually promote HIE usage more in the segment of IDS physicians than in the non-IDS physician segment.

Further, a HIE provides real-time information sharing capabilities with persistent databases. In the current context, HIE provides this support to interacting physicians in referrals and as a result, we expect to see greater levels of such engagement among physicians participating in HIE. Extending this phenomenon to the broader context of IT, we note that any IT innovation with such capabilities would improve the efficiency of the interactions among the people in the processes supported by it. As a result, we could expect the level of interactions among the users of such IT to increase over time. This logic follows the assortative mechanism in which the changes induced by IT in the behavior of its user entities is explained by the compatibilities and complementarities among them. Furthermore, we could expect this behavioral change to be higher when the need for the capabilities of the IT innovation are more pronounced. Empirical investigations of these expectations with different IT innovations are interesting directions for future research.

Future Research: A rich agenda for future research emerges from the results of this study. First, although the referring physicians essentially make the referral choices, we acknowledge that the patients could also impact this decision. This has also been observed in our exploratory field study. While HIE is a factor affecting the referral choice from a physician's perspective, it is not clear whether it is also a factor from the patient's perspective. We could not include the patients' effect in our analysis since the information on patients was not available from the CMS dataset. So, a study where data on patients who were referred among the physicians can be collected would lead to a deeper understanding of the impact of patients attributes and their preferences in the referral choices in conjunction with the physicians' preferences due to HIE. Second, we expect the patients' outcomes to be improved as a result of the shifts in referrals to HIE members. This expectation is based on the following reasons. Note that the extant literature has shown the positive impact of HIE usage on the patients' outcomes. Further, our exploratory field study revealed the potential positive impact of HIE-based referrals on patient satisfaction, leading to greater reputation of the physicians among the patients. Thus, studying whether shifting referrals to HIE members lead to positive patient outcomes such as patient satisfaction is an interesting and important research question for future study. Third, because we used Medicare data to identify referrals among physicians, the generalizability of our findings to referrals with regard to younger patients needs to be investigated. Referrals among physicians for younger patients may be different from what we observed in this study with Medicare patients. Fourth, future studies that explore the impact of HIE adoption on referral patterns at the patient level are important. This will allow researchers to examine the impact of patient characteristics and the complexity of the required care on physicians' referral decisions. Care complexity is a well-recognized concept that describes the level of care intensity, workload and specialized skills needed in healthcare (Guarinoni et al., 2015). As the level of care complexity grows, the need for timely, accurate and complete information sharing among the care providers becomes greater. As a result, the need to decrease the transaction costs in referrals is much stronger and the capabilities of the HIE would be even more valuable to the concerned providers. We thus expect stronger motivations for its members to refer to other members, and consequently we expect a bigger shift of referrals towards HIE members when the care complexity is higher. Fifth, given the importance of the referrals, identifying dominant drivers of the current referral processes which may indicate inefficiencies in referral processes is in particular of interest to healthcare policy makers. Sixth, studies focusing on the strategies of technology-enabled referral management services which are currently in a stage of infancy are important directions for future research. Seventh, we would like to note that we only had data on HIE adoption, and did not have any data on HIE usage. This requires a measurement of the physicians' perceptions and the difficulties of HIE usage in practice, leading to a future study on actual HIE usage and referrals. Finally, study of healthcare markets with multiple competing HIE platform and their influence on referrals is a worthy endeavor for future research.

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Appendix 1. Network Analysis

SIENA Modeling Framework

SIENA is a statistical tool designed to analyze longitudinal network data, i.e., two or more sets of network observations over time (Ripley et al., 2015; Snijders et al., 2010). It incorporates different variants of a dynamic network model family: the Stochastic Actor-Oriented Model (SAOM) (Snijders et al., 2010). SIENA allows to concurrently model changes in a network and an attribute as separate dependent variables, termed as co-evolution model. To model each dependent variable, a variety of explanatory variables, which are called *effects*, are used. The objective of SIENA is to estimate a parameter for each effect to express the importance of the effect on the dependent variable. Based on the defined effects, an iterative stochastic simulation algorithm is applied to find the parameters. Specifically, given two waves of a network observed over time, the model assumes that the transition from the observed network at the first point of time to the second point is decomposed into very small steps. In each mini-step, one actor is randomly chosen, and is given the opportunity of at most one change in one of the dependent variables. If the selected dependent variable is the network, then the chosen actor evaluates all possible outcomes of at most one change in her links to decide whether an outgoing link should be created, dropped, or maintained. If the selected dependent variable is the attribute, the chosen actor evaluates all potential outcomes of at most one level change in the attribute to decide whether her attribute level should be increased, decreased, or kept at the previous level. The evaluation of changes is based on an objective function. An actor, in a given mini step, typically chooses an action that maximizes her objective function (Snijders et al., 2010). The general form of objective functions for network and attribute changes are respectively presented as follows:

$$f_i^{net}(x,z) = \sum_k \beta_K^{net} s_{ik}^{net}(x,z)$$
$$f_i^{beh}(x,z) = \sum_k \beta_K^{beh} s_{ik}^{beh}(x,z)$$

In the above equations, the superscript *net* is used to indicate that the objective function models the network changes, and the superscript *beh* is used to indicate that the objective function models the attribute changes. Variables x and z denote the network and the attribute, respectively. β_K^{net} and β_K^{beh} represent the parameters corresponding to the effects $s_{ik}^{net}(x,z)$ and $s_{ik}^{beh}(x,z)$. SIENA estimates the parameters to represent the extent to which the corresponding explanatory variable affect the objective function. Further specifications of SIENA are described by Ripley et al. (2015).

We concurrently model the *referral network* and *HIE adoption* as two separate dependent variables. Referral network is defined as a directed network in which a node represents a physician and a link represents a referral. Specifically, the link x_{ij} is equal to 1 if there is referral from physician *i* to physician *j*, and zero otherwise. The dependent variable HIE adoption (*HIE*) is binary, and is equal to 1 for physicians who have adopted HIE, and zero otherwise. To test the impact of HIE adoption on referrals, we include the effect "HIE similarity", defined as interaction of ego's and alter's HIE, and to test the impact of referrals on HIE adoption, we include the effect "number of outgoing links to HIE members", and "number of incoming links from HIE members". For simplicity we refer to them by "outgoing links to HIE members", and "incoming links from HIE members" respectively. Specifically, the effect "HIE similarity" is a representation of social selection in our context and the effects "number of outgoing links to HIE members", and "number of incoming links from HIE members" represent the social influence. We control for the effects density, reciprocity, popularity, experience, gender similarity, HIE ego, and HIE alter in modeling the referral network. We control for the effects of out-degree and in-degree centrality, and ERX, EHR, PQRS, and size of the practice in modeling HIE adoption.

Results

The dataset prepared for this analysis consisted of the referral network among physicians with the following specialties in the Buffalo HRR: internal medicine, family medicine, cardiology, pathology, pulmonology, radiology, and nephrology. Among 60 different types of specialists, these are the most frequent ones who contribute to 70% of the links in the referral network over the period of our study. We restricted our analysis to these certain specialties to yield a sharper focus on the most important specialties in the referral network and also improve the computational performance of SIENA. The resultant dataset has 486 physicians.

Using SIENA, we could analyze the entire time horizon 2009-12 using any chosen sequence of adjoining (T1, T2) configurations. In our analysis, we chose T1 and T2 as the consecutive waves in the time period 2009-2012. The models are implemented using the Rsiena package (V.1.2-25) in R. In all models, the Jaccard index, which is a value that shows the proportion of stable links between two the consecutive waves, is between 0.57 and 0.60. These values are considered to be good for modeling the changes (Ripley et al., 2015). Estimations are based on the Method of Moments and 4000 simulations in phase 3 of the SIENA algorithm where the significance of the effects is determined. All models converged according to the t-ratios for convergence and the overall maximum convergence ratio criteria indicated by Ripley et al. (2015).

Table A1 shows the estimation results of the co-evolution model for the pairs of consecutive-year waves. The parameters are significant in all models except for the consecutive years 2009 and 2010. This could be due to a small percentage of HIE adopters in year 2009, when the HIE system was just introduced in the region. The significantly positive parameter for *HIE similarity* shows that physicians who are HIE members have a higher odd of linking with HIE member than non-members. This finding is consistent with our findings in the main paper about the impact of HIE adoption on referrals. The significantly positive parameter for the *outgoing links to HIE members*, or *incoming links from HIE members* indicate that non-

HIE member physicians who are linked to a larger number of HIE members in the referral network, are more likely to adopt HIE than other physicians. Finally, the overall impact of the explanatory variables is estimated using the four waves of the data for the consecutive years 2009, 2010, 2011, and 2012. The corresponding results are consistent with our findings, and are presented in Table A2.

Note that we cannot estimate the model when both *outgoing links to HIE members* and *incoming links from HIE members* are included in the model. This is due to the high collinearity between them, which also leads to large standard errors of those estimates (Ripley et al., 2015). We thus estimate two separate models, each time by including one of these effects. Although we acknowledge this limitation, we argue that our co-evolution model is still capable of serving not only as a robustness test for our main hypotheses of the paper, but also producing insights with regards to mutual association between HIE adoption and referrals patterns. Specifically, the reason is that we have observed a significant impact of HIE adoption on the referrals while controlling for the impact of referral patterns on HIE adoption through either of *Outgoing links to HIE members* or *Incoming links from HIE members.*

Table A1. Parameter Estimation (Standard Errors) of the Co-evolution Model Using Two Waves of Data

Variable	**2009-2010**		**2010-2011**		**2011-2012**	
Referral Network						
HIE similarity	0.114 (0.339)	0.101 (0.337)	1.822*** (0.347)	1.800*** (0.346)	1.236*** (0.157)	1.251*** (0.142)
HIE Adoption						
Outgoing links to HIE members			0.886** (0.430)		0.380** (0.186)	
Incoming links from HIE members	2.027 (2.083)	1.868 (3.467)		0.857** (0.330)		0.398** (0.201)
Convergence ratio of the Model	0.185	0.106	0.133	0.145	0.176	0.138

****: P-value<0.001, **: P-value<0.05, *: P-value<0.1*

Table A2. Parameter Estimation (Standard Errors) of the Co-evolution Model Using Four Waves of Data

Variable	**2009-2010-2011-2012**	
Referral Network		
HIE similarity	0.938*** (0.106)	0.938*** (0.103)
HIE Adoption		
Outgoing links to HIE members	0.399** (0.128)	
Incoming links from HIE members		0.394*** (0.112)
Convergence ratio of the Model	0.217	0.171

****P-value<0.001, **: P-value<0.05*

Appendix 2. Summary of the Content Analysis Findings

Code	Category	Theme
Sending ADT information to patients' providers Saving phone calls for patients' records follow-up Saving outgoing faxes of patients' information Reducing waiting time for receiving information of incoming patients Saving time and money for physicians as data is available Providing timely test results back from the referred physician Fast availability of lab results compared to burning CDs Patients' satisfaction due to fast and easy availability of lab results	HIE data is fast and easy to access	T1: HIE is better than existing channels in referrals
Getting patients' information directly from the hospitals Accessing information from multiple sources Patient's pre-visit planning by physicians Providing clinical records to physicians without patients' bias Patients' information may get lost while sending through other channels Accessing a lot of past information on patients Patients' clinical information is huge	HIE data is complete	
Eliminating duplication of tests	HIE data is up-to-date	
No clear mechanism for directly sending clinical notes Manual downloads from HIE may not be easy Referred HIE-member is unaware of HIE services and keeps requesting	Operational challenges of HIE	T2: HIE services have some limitations
Adding prescription to lab orders would be advantageous	HIE services can be improved	
Physicians going to the same country clubs Trust in the referred physician Referral agreements among physicians	Physicians have relationships	T3: Factors other than HIE could keep existing referral wheels turning
Providing the best care for the patient Referring to the most popular physicians	Clinical expertise is important	
Patient's preferences on some doctors	Patients express preferences	
Not too many physicians available to refer to	Referral options are limited	
Saving billing dollars to patients by avoiding repeated procedures	HIE saves billing dollars for patients	T4: HIE saves money for patients
Tracking and complying with measures of health insurance companies Easy reporting of public health measures	HIE helps with reporting measures	T5: HIE helps in complying with regulations
HIE integrates with EMR system and enhances its benefits	HIE integrates well with local systems	T6: HIE has integration capabilities