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Do Health Information Exchanges Deter Repetition of Medical Services?

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Repetition of medical services by providers is one of the major sources of healthcare costs. The lack of access to previous medical information on a patient at the point of care often leads a physician to perform medical procedures that have already been done. Multiple healthcare initiatives and legislation at both the federal and state levels have mandated Health Information Exchange (HIE) systems to address this problem. This study aims to assess the extent to which HIE could reduce these repetitions, using data from Centers for Medicare & Medicaid Services and a regional HIE organization. A 2-Stage Least Square model is developed to predict the impact of HIE on repetitions of two classes of procedures: diagnostic and therapeutic. The first stage is a predictive analytic model that estimates the duration of tenure of each HIE member-practice. Based on these estimates, the second stage predicts the effect of providers' HIE tenure on their repetition of medical services. The model incorporates moderating effects of a federal quality assurance program and the complexity of medical procedures with a set of control variables. Our analyses show that a practice's tenure with HIE significantly lowers the repetition of therapeutic medical procedures, while diagnostic procedures are not impacted. The medical reasons for the effects observed in each class of procedures are discussed. The results will inform healthcare policymakers and provide insights on the business models of HIE platforms.

CCS Concepts: • **Information systems → Information systems applications**

Additional Key Words and Phrases: Health information exchanges, repetition of medical procedures, 2sls model, healthcare quality, healthcare cost, diagnostic procedures, therapeutic procedures

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1. INTRODUCTION

A substantial part of the U.S. structural deficit is spent on healthcare expenses [Chernew et al. 2010]. The United States spent 17.9% of its GDP on healthcare in

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2010, more than any other country in the world [Baicker and Skinner 2010]. However, based on comparative analyses, the U.S. has been shown to underperform other countries on most dimensions of healthcare performance [Davis et al. 2010]. Prior studies have revealed that the significant amount of the U.S healthcare expenses arise from inefficient utilization of medical services, whereby many diagnostic tests, treatments, and other forms of care are performed with little consideration to the value that they provide for the patients [Berwick and Hackbarth 2012; Garber and Skinner 2008]. According to the Congressional Budget Office, the cost of the medical procedures that do not actually improve the quality of health outcomes is estimated to be around $700 billion per year, or 5% of the U.S. GDP [Bardhan et al. 2014]. These unwanted expenses arise in many cases such as avoidable hospitalizations, unnecessary admissions of patients with chest pain, and overuse of imaging procedures, as well as overuse of certain surgeries [Bentley et al. 2008; Orszag 2008b].

Given this, as a national effort to improve the quality of healthcare and reduce the associated costs, Information Technologies (IT) have been employed in the healthcare systems [Aron et al. 2011; Buntin et al. 2011]. The recently enacted Health Information Technology for Economic and Clinical Health Act (HITECH) demands all medical records to be organized in standardized digital forms [Blumenthal and Tavenner 2010] and aims at setting up Health Information Exchange (HIE) platforms, through which healthcare providers can easily share and access patients' clinical information [Sipkoff 2010].

Since the enactment of HITECH, HIEs have become integral parts of the national healthcare reform [Vest and Gamm 2010; Vest et al. 2011b], primarily because of their promise of improved patient care and enhancement of the quality of healthcare services. HIE is a potential solution to persisting problems in the U.S. healthcare system, including cost [Overhage et al. 2002; Walker et al. 2005; Frisse et al. 2011; Vest et al. 2014], safety [Bloom 2002], and efficiency [Corrigan et al. 2002]. An HIE is intended to enable timely access to medical records and help physicians make better decisions, save more lives, and reduce huge costs by avoiding redundant tests, hospital re-admissions, or wrong diagnoses.

A central motivation for the concept of HIE is to enable medical providers to access recent and relevant clinical information at the point of care. In the absence of HIEs, the non-availability of clinical information adversely affects the clinical quality and economic efficiency of healthcare services [Forster et al. 2003; Kohn et al. 2000]. This non-availability of clinical information is often attributed to the lack of access to the data that may be available at different locations rather than an absence of the pertinent data itself per se [Forster et al. 2003]. The missing information is often clinically important, and its absence can result in harm to patients [Forster et al. 2003; Kohn et al. 2000]. Lack of access to previous medical history leads to an increase in duplicate tests for patients obtaining care at multiple settings [Bardhan et al. 2014]. For example, consider a diagnostic or therapeutic setting where a healthcare provider needs the result of a certain test on a patient. Assume that the test has been done in the past, and its result is still valid but unavailable at the current setting. Hence, the provider will re-order the test on the patient. Redoing medical tests may put the patient at more risk and also increase cost of healthcare. Reducing unnecessary medical tests has been cited as critical in reducing the overall health care costs in the U.S. [Berwick and Hackbarth 2012; Fries et al. 1993]. In the healthcare settings, more efficient medical care most often results in both lower costs and higher quality at the same time. Take the repetition of medical procedures as an example. If HIE reduces repetitions, then it has an immediate impact on reducing the cost of care, while also increasing the quality of care by helping avoid delays caused by repeated testing, and avoiding unnecessary risks associated with some tests. Prior research indicates that implementation of information sharing technologies in healthcare systems reduces the cost (through reducing the repetition of medical procedures) and can at the same time increase the quality of care (by reducing the frequency of readmissions) [Bardhan et al. 2014, 2011].

HIE platforms enable electronic sharing of clinical information with providers and organizations across the continuum of care. This information sharing allows medical providers at a given point-of-care to access patient data about encounters that have occurred at other points-of-care [Vest et al. 2015]. Availability of previously inaccessible data through HIE results in more comprehensive clinical information and potential improvement of quality of care [Branger et al. 1994; Kaelber and Bates 2007; Smith et al. 2005].

Few studies have shown that HIE can reduce performing of unnecessary medical procedures during patient care. Bailey et al. [2013] show that HIE is associated with decreased diagnostic imaging. Lammers et al. [2014] also found evidence suggesting that HIE reduces repeat imaging among patients visiting multiple emergency departments. Recently, Yaraghi [2015b] found evidence that HIE usage is associated with reduction in the expected total number of laboratory tests and radiology examinations ordered per patient at the emergency department (ED). While these studies have shown that HIE can reduce unnecessary medical procedures during patient care, they have some restrictions that need to be addressed. First, most of them focus mainly on the diagnostic medical procedures performed in the ED. To best of our knowledge, the impact of HIE has not been examined in the office setting. The difference in the setting in which HIE is being used could lead to different outcomes. In particular, the medical encounters in physician offices are usually scheduled and thus non-urgent, while those that happen in EDs are, by definition, urgent. The urgency of the patient conditions in the EDs leads physicians to make clinical decisions in the shortest amount of time, with the bare minimum of available medical history. To do so, ED clinicians use HIEs to access the results of prior diagnostic procedures and save time by avoiding new ones. On the other hand, in the office settings, since medical decisions are less time sensitive, physicians may prefer to have access to the results of most recent diagnostic procedures and thus, despite having access to older ones, they tend to repeat the diagnostic procedures in order to enhance the quality of their medical decisions. Second, these studies looked at a limited set of medical procedures. For example, Bailey et al. [2013] have considered the impact of HIE on repetition of only diagnostic neuroimaging (computed tomography (CT), CT angiography, magnetic resonance imaging (MRI), or MRI angiography), and Lammers et al. [2014] have considered only three common types of imaging tests (CT, ultrasound, and chest x-ray). Third, their results are obscured by confounding factors, factors that impact both HIE adoption and repetition of medical procedures yet unaccounted for [Yaraghi 2015a]. More importantly, other physician- or practice-related variables could moderate the impact of HIE usage on medical outcomes. For example, membership in quality auditing programs could entice physicians to rely more on health IT and thus may bolster the benefits of HIE. However, to the best of our knowledge, prior research has not examined factors that could enhance or impede the possible benefits of HIE systems.

To address these limitations, we study the impact of HIE on diagnostic medical procedures as well as therapeutic medical procedures performed in the office setting. Our findings are more robust as we look at a larger number of medical procedures. Our study examines the overall HIE impact on 110 types of diagnostic procedures as well as 97 types of therapeutic medical procedures. Finally, we study the impact of more factors such as geographical regions, quality reporting programs, and other health IT tools on the repetition of medical procedures.

To support the ongoing efforts by policymakers and administrators to streamline and promote HIE platform services, that substantial savings can be achieved from

HIE should further be examined. The current research examines the impact of HIE on reducing repetitions of medical procedures. In addition, we analyze how participation of physicians in federal audit and quality assurance program as well as the level of complexity of medical services may impact the relationship between HIE and repetition. This study is supported by publicly available datasets from the Centers for Medicare & Medicaid Services (CMS) and HEALTHeLINK, the regional HIE serving western New York. The key results of this study can be summarized as follows. Classifying procedures into *Diagnostic* and *Therapeutic* using inputs from physicians and clinical literature, we first show that HIE has a statistically significant impact on reducing repetitions in therapeutic procedures. Second, we show that the participation in the audit program and medical complexity significantly moderate this effect. Next, these effects are seen to be not significant in Diagnostic settings. Finally, we provide clinically intuitive interpretations of these effects, leading to policy implications for HIE development with concurrent and integrative consideration of audit and quality assurance programs and medical services complexity. These implications apply to administrations ranging from the federal to the regional.

The organization of this article is as follows. Section 2 reviews the related literature. Section 3 examines the drivers and barriers of procedural repetitions and presents our research hypotheses. Section 4 discusses the data sources and the attribute schema, and Section 5 presents a 2-Stage Least Square (2SLS) model of repetition deterrence. Section 6 presents the logic and structure of the medical procedures classification, and Section 7 presents the empirical results. Finally, Section 8 discusses the managerial and policy implications of this study and the conclusions.

2. RELATED LITERATURE

In the following discussion, we briefly review two streams of studies in the literature that are related to the current research context.

2.1. Reasons for Medical Services Repetition

The Committee on Quality of Healthcare in America of the Institute of Medicine defines *overusing* of healthcare services as the use of healthcare resources and procedures in the absence of evidence that such usage could help the patients involved. The reasons for repeated medical procedures have been analyzed extensively in many studies [Kwok and Jones 2005]. Over-ordering of tests may be the result of the inexperience of healthcare professionals and/or their lack of knowledge about the appropriate uses of tests [Wong 1995]. Failure to check previous results of medical services due to huge or complex and disorganized patient files is cited as another important reason for repeating medical procedures [Tierney et al. 1987]. Over-ordering of medical services can also arise from non-user friendly electronic medical record systems or fear of errors of omission and litigation [Tabriz et al. 2004]. Moreover, patients could also actively ask for repeated tests and often attach greater value to test results than what is justifiable [McDonald et al. 1996]. These studies broadly indicate three drivers of repetition: *providers' inexperience, non-availability of timely and relevant past information* and *environmental influences*. Besides these, repetitions due to *medical necessity* are relevant, and anecdotal evidence suggests the occurrence of repetitions due to *financial incentives* to healthcare providers who get compensated for these services, as well as *non-subscription* to federally administered quality assurance programs by healthcare providers.

2.2. Health Information Technologies: Effects, Adoption, and Usage

The implementation of IT tools significantly improves the performance of healthcare systems and the health of patients. The obvious benefit of health IT has been established in improving administrative functions, such as decreasing paperwork and the workload of healthcare providers and enabling easy access to information such as a patient's medical history [Hillestad et al. 2005]. Health IT significantly contributes to preventing medical errors by enforcing clinical standards and care protocols [Bates et al. 1998]. Health IT makes information more organized and easier to track, which increases accuracy. A significant number of studies have shown the impact of health IT on the quality, efficiency, and the reduction of the cost of care [Buntin et al. 2011; Chaudhry et al. 2006; Jamal et al. 2009; Shekelle et al. 2006]. The major benefit of health IT is a reduction in the utilization of medical services. Jamal et al. [2009] systematically review the evidence on health IT benefits and conclude that the implementation of IT tools in healthcare systems increases adherence to guidelines, enhances disease surveillance, and decreases medical errors. In sum, the use of IT tools in the healthcare domain has the potential to enable a drastic improvement in the delivery of care by making it faster, safer, and more efficient.

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

Yaraghi [2015a] and Yaraghi et al. [2013, 2014a, 2014b] are some of the earliest research on the adoption, usage, and effectiveness of HIE systems. These works have also been supported with data by HEALTHeLINK. Yaraghi et al. [2013] consider HIE a multisided platform and estimates the network externalities of adoption by the primary-care and specialist physician communities. They model the intra- and inter-community diffusion processes by generalizing the well-known Bass diffusion model to group-level adoption. Yaraghi et al. [2014b] investigate these diffusion processes across rural and urban geographical domains and medical specialty groups. Using a social network analysis of physician networks and patient networks, Yaraghi et al. [2014a] examine the drivers of adoption, usage, and the involvement of clinical practices in the co-production of HIE services. They show that adoption and usage are influenced by networks of physicians and patients, isomorphic effects of large practices on the smaller ones, and practice labor inputs in HIE use. This is a longitudinal study of actual adoption and usage behaviors of 2,054 physicians within 430 community medical practices in western New York. Yaraghi [2015b] demonstrates the impact of HIE on reducing procedural repetitions in emergency departments in a randomized controlled trial.

3. DETERRENTS OF REPETITIONS

While the reasons for repeating medical procedures can be multi-fold, certain institutionalized as well as clinically driven deterrents to this practice exist. In the following discussion, we develop a model of deterrence using participation in HIE and federally administered audit and quality assurance programs as the institutionalized factors and medical service complexity as a clinical factor.

3.1. Health Information Exchanges

As discussed in the earlier sections, HIEs have become central to improving the cost-effectiveness of the U.S. healthcare system. Potential savings from HIEs are expected as a result of reducing unnecessary utilization that occurs when patients visit multiple providers who lack the ability to access patients' recent medical history [Orszag 2008a]. HIEs provide appropriate, up-to-date, and relevant patient-specific information at the point of care and, consequently, reduce the level of repetition in medical services rendered. This specifically addresses the non-availability reason cited for repetitions. When a service provider accesses the HIE, the repetition of a service can be avoided by following one of the three paths: Information on the past performance of the exact service is available, information from other types of relevant medical services points towards avoidance, or a combination of both. So we hypothesize that providers who have access to HIE are less likely to repeat medical procedures. Like other information systems, the users' experience with HIE increases their ability to effectively use the service.

Users of information technologies will change gradually from novices to skilled users of the system [Davis et al. 1989]. Through experience with a new IT artifact, participants' involvement in the system increases, and they adjust their perceived ease of use of the system [Davis et al. 1989; Fazio and Zanna 1978; Fazio et al. 1978; Venkatesh and Davis 2000]. Specifically, in regard to the HIE system, Yaraghi et al. [2014a] study the impact of experience on increasing the productivity of HIE members. They conclude that during the post-adoption period, HIE participants acquire more knowledge and skills to use HIE. They propose that HIE members gradually learn to use HIE more efficiently through their acclimatization to the system and through communicating with other participants. Figure 1 presents a screenshot of the user interface of the HIE system studied in this article and depicts the level of complexity that clinicians must overcome while using the system. This screenshot has been provided by HEALTHeLINK. The personal identification information in this screenshot is not real. For privacy reasons, the original personal identifiers are not disclosed.

More importantly, successful implementation of HIE in the office settings requires adequate integration with the usual workflow of the physicians' offices. Uses should not only learn how to use the system, but they should also learn how the efficiently integrate the system into their daily routines and how to optimally use the HIE system along with the other health IT products (such as EHRs) that are already available to them.

To summarize, as the HIE tenure of a provider increases over time, his or her level of experience with the platform technology increases, resulting in decreasing propensity to repeat procedures. This is formally stated in Hypothesis 1 below.

Hypothesis 1: Tenure with HIE reduces the repetition of medical procedures.

3.2. Audit and Quality Assurance

As the central motivation of HIE is to enhance the quality of care, it is desirable to study the impact of HIE in the presence of other managerial policies intended to improve health outcomes. In the report published by the Massachusetts State Auditor [2013], internal controls, including regulations, policies, and procedures, have shown to be important to address the concerns of the state's Medicaid program about unnecessary redoing of medical tests. Auditing programs and physician education on cost of medical services are important solutions that could be implemented to control overutilization of medical services [Miyakis et al. 2006]. Quality measurement and public reporting in the U.S. healthcare system are intended to facilitate targeted outcome improvement, practice-based learning, shared decision making, and effective resource utilization [Bekelis et al. 2015].

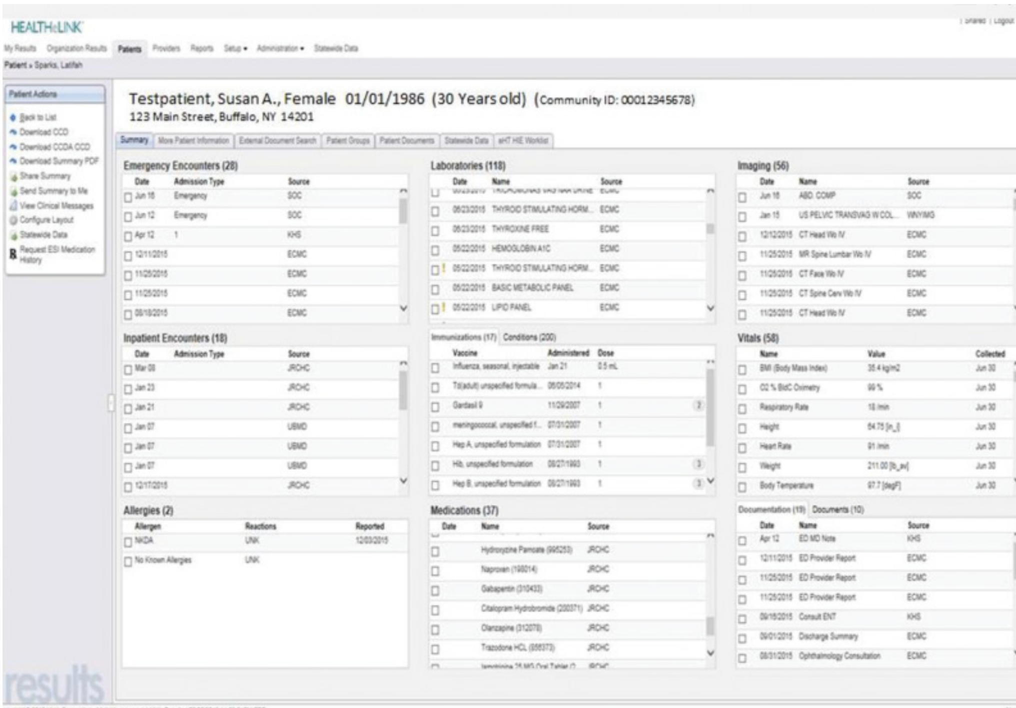

Fig. 1. A screenshot of the HIE user interface (the original personal identifiers are not disclosed).

CMS has several quality initiatives that provide information on the quality of care across different settings, including hospitals, skilled nursing facilities, home health agencies, and dialysis facilities for end-stage renal disease. CMS believes that these quality initiatives aim to empower providers and patients with information that would support the overall delivery and coordination of care and ultimately would support new payment systems that reward physicians for providing improved quality of care rather than simply paying based on the volume of services.

Under the Tax Relief and Health Care Act of 2006, CMS implemented the Physician Quality Reporting Initiative, now called Physician Quality Reporting System (PQRS), with a bonus payment of 1.5% for successful participation based on the estimated total allowed charges for all cover services during the reporting period [AMA 2015]. PQRS participants report well-defined quality measures of the care that they deliver to the Medicare beneficiaries. The quality measures are meant to reflect the ability of physicians and clinical teams to provide high-quality care. CMS has established that quality measures should relate to one or more of the following goals: effective, safe, efficient, patient-centered, equitable, and timely care [Bekelis et al. 2015]. Given the increasing importance of PQRS program in the national healthcare debate, analyzing its interaction with HIEs will enable policymakers to better evaluate the costs and benefits of this program.

Dowd et al. [2016] indicate that physicians who participate in PQRS find themselves in a new monitoring environment. The monitoring environment impacts the behavior of healthcare providers and thus impacts clinical outcomes. They show that PQRS participants avoid inappropriate utilization of healthcare services. Given this, we postulate that providers who participate in PQRS avoid performing unnecessary medical procedures for their patients, which results in improving the quality of care and decreasing healthcare costs. For this reason, we expect that this reporting program, PQRS, affects the way HIE reduces repetition of medical procedures. We believe that the volume of the medical services provided by PQRS participants is already so condensed due to the stringent reporting requirements that HIE will not make a remarkable difference in terms of reducing repetition of medical procedures. This implies that the focus on avoiding repetitions due to PQRS participation will limit the effect of HIE on reducing repetitions. Hence, HIE is less needed for reducing repetitions by PQRS participants than non-participants. We formally state this argument in Hypothesis 2 below.

Hypothesis 2: PQRS participation moderates the impact of HIE tenure on level of repetition, such that HIE impact on decreasing repetition is more for HIE members who do not participate in PQRS than for HIE members who also participate in PQRS.

3.3. Complexity of Medical Services

There are many studies that examine the decision-making process in the medical context. In general, many factors such as patients' family medical history, patients' information about a disease, and patients' risk preferences impact the patients' decisions in the process of care and may influence the pursuit of preventative health behaviors as well as treatments [Katapodi et al. 2004; Lloyd 2001; Mazur et al. 1999; Sivell et al. 2008]. In particular, the patients' choice of medical services such as surgery or radiotherapy can be strongly influenced by their perceived risk of those tests [Lloyd 2001]. A nationwide survey conducted by Zikmund-Fisher et al. [2010] suggests that the cost of medical services is also one of the important factors that most of the U.S. adults consider when they decide about receiving a medical service. Based on these studies, we argue that when patients have a choice between two medical procedures with different risk levels and equal outcomes, they will be reluctant to undertake the more complex medical services, because they would be often seen as more risky and costly than less complex ones.

This analysis of risks and benefits is not limited to patients. The literature has shown that healthcare providers assess the benefits and risks of medical procedures before planning and performing them. The exposure of patients to complex medical procedures may lead to more severe negative outcomes such as pain, longer recovery periods, prolonged incapacitation, and even an increased risk of mortality. To help medical providers to assess such risks better, several decision support systems have been developed. For example, Pauker and Kassirer [1975] present a risk-benefit framework for assessing the health-related utility of genomic tests, and Veenstra et al. [2010] have developed a framework for analyzing the costs and benefits of therapeutic procedures. Therefore, we contend that physicians will carefully examine the risks and benefits of medical procedures, especially the more complex medical procedures that are more likely to lead to potentially severe complications.

Moreover, payers, including Medicare, require physicians to obtain prior authorization for certain types of medical procedures to ensure medical necessity. Generally, these procedures are either riskier for patients or are more expensive for insurance companies. The authorization process requires related documentation to be submitted for review before physicians perform the medical procedures and submit the claims. The burdens of obtaining authorization of insurance companies before performing complex medical procedures leads physicians to be more cautious and thus consider potential alternatives to such procedures before deciding on a course of action.

Given these explanations, we believe that physicians as well as patients are more cautious when they decide about a complex medical procedure and therefore are more likely to rely on HIE to make better decisions. Therefore, we expect the complexity of medical procedures to moderate the effect of HIE tenure on decreasing repetitions. The reason is that providers are more willing to use the information on the patients available through the HIE when they decide about performing more complex procedures. Consequently, we expect that after using HIE, it is less likely that the provider would decide to perform the procedure again. In the other words, as the complexity of medical procedures increase, the HIE impact on reducing the repetition increases. So we hypothesize that complexity buffers the effects of HIE on repeating medical procedures. In the other words, the relationship between HIE and repetition is conditioned on the complexity of medical procedures. We formally state this argument in Hypothesis 3 below.

Hypothesis 3: Level of complexity of medical services moderates the impact of HIE tenure on level of repetition such that HIE impact on decreasing repetition is more when complexity is high than when complexity is low.

4. DATA SOURCES AND SCHEMA

CMS is a federal agency within the U.S. Department of Health and Human Services. It administers the Medicare program and works in partnership with state governments to administer Medicaid, the State Children's Health Insurance Program, and health insurance portability standards [CMS 2016]. Medicaid and Medicare data available from CMS are widely used for epidemiological studies, health services, and policy research [Platt and Ommaya 2005; Ray 1997]. Medicare claims have been analyzed by health service researchers and medical decision analysts to examine clinical outcome of patients as well as mortality trends among Medicare beneficiaries [Ash et al. 2003; Peter et al. 2008]. Medicare claims data has also been used to measure resource inputs, utilization, and Medicare spending. Wennberg et al. [2004] use Medicare claims data to monitor providers' performance among patients with severe chronic illness. Brown et al. [2002] estimate treatment cost for colorectal and breast cancer, including estimates of average cost per patient by the initial, terminal, and continuing care phases of cancer treatment in Medicare beneficiaries in the U.S. Similar CMS data-driven studies in a variety of both clinical and policy-level settings are several.

This study is based on four datasets: (i) Medicare Provider Utilization and Payments data, (ii) Physicians Compare data, (iii) HIE enrollment data on the members of HEALTHeLINK, and (iv) U.S. National Census database. The first two datasets are from CMS, and they are publicly available. The HIE data are from HEALTHeLINK and are also publicly available. For simplicity, we denote the three datasets as MPUP, PC, HLINK, and CENSUS, respectively.

CMS has released the *Medicare Provider Utilization and Payments dataset* for the calendar years 2012 and 2013. This dataset describes the medical services provided to Medicare beneficiaries by all healthcare providers throughout the U.S. For each provider, this dataset identifies the type and number of times that a medical service has been performed. It also identifies the number of unique Medicare patients who received a particular medical service from a provider. Comparing the total number of times that a provider has performed a service with the total number of unique patients who have received that service from the given provider, we can determine the number of repetitions for each medical service performed by each provider. Each record of the MPUP dataset is indexed on the key {NPI, SCI}, where NPI is the National Provider Identifier and SCI is the Service Code Identifier. The *Physician Compare dataset* shows additional practice-level characteristics such as participation in Electronic Prescribing (ERX) Incentive program and the PQRS as well as their affiliation with medical practices and graduation year from medical school. Each record of the PC dataset is indexed on {NPI, PID}, where PID is the Practice Identifier. The HEALTHeLINK membership data are available at their website [HEALTHeLINK 2016], where each record is indexed on the names of member physicians and their practices.

Table I. Practice-Specific Attributes

PID: Practice Identifier (*Source:* PC)
ERX: Binary; equals 1 if the practice is participating in the Medicare Electronic Prescribing (eRx) Incentive program and zero otherwise. This program encourages physicians and other professionals to use electronic prescribing to improve communication, increase accuracy, and reduce errors (*Source:* PC).
EHR: Binary; equals 1 if the practice is participating in EHR incentive program and zero otherwise. In this program, Medicare provides incentives and payment adjustments to eligible professionals who use certified EHR technologies in ways that improve healthcare (*Source:* PC).
PQRS: Binary; equals 1 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 (*Source:* PC).
Urb: Binary; equals 1 if the practice is located in an urban area and zero otherwise (*Source:* CENSUS)
HIE: Based on the date of HIE adoption from the HEALTHeLINK database, we created the HIE variable for each practice. This variable is set to zero for practices that are not HEALTHeLINK members. For HEALTHeLINK members, this variable is set equal to the number of months since their date of adoption until January 2012 while analyzing the 2012 Medicare Provider Utilization and Payments dataset, and until January 2013 in analyzing the 2013 dataset. In addition, as we do not have the exact dates of the claims submitted by healthcare providers, we eliminated those practices that joined HEALTHeLINK during 2012 when analyzing the claims data of 2012. Similarly, when analyzing the claims data of 2013, we eliminated those practices that joined during 2013 (*Source:* HLINK).
NOP: Number of providers affiliated with a practice; indicates the size of the practice (*Source:* PC).

Table II. Physician-Specific Attributes

NPI: National Provider Identifier (*Source:* MPUP).
EXP: Number of years of experience a provider has in the practice (*Source:* PC, MPUP).
Gender: Gender of the provider (*Source:* MPUP).
AMA: Average Medicare Allowed Amount for a service; This specifies the sum of the amounts paid by Medicare, the deductible and coinsurance amounts that the beneficiary is responsible for paying, and any amounts that a third party is responsible for paying. Although it is mainly determined by the type of service, it may vary among different providers for a specific service (*Source:* MPUP).

In the preparation of the dataset for our analysis, we first merged the datasets MPUP and PC based on NPI. Next, the resulting dataset was joined with the HLINK dataset based on the names and addresses of medical providers in western New York, who constitute the target population of physicians in this research. The attributes projected and aggregated after merging these sources can be organized into two distinct sets: *Practice-Specific* and *Physician-Specific*. These sets are briefly described in Tables I and II below.

We employ "Medicare allowed amount" in the CMS dataset to measure complexity. According to the definition provided by CMS, Medicare allowed amount is the sum of the dollar amounts that the providers can be paid by Medicare, patients, and other insurances. This variable is measured by CMS using a Resource-Based Relative Value Scale (RBRVS). The RBRVS was created to provide a standard system of pricing that weighs physicians' services according to the resources used in delivering the service. The total cost assigned to a service is a combination of three components: a "physician work" component, a "practice expense" component, and a "malpractice expense" component [Buntin et al. 2004]. Costs associated with each component are given a weight, or index value, and are adjusted for local differences [Maxwell and Zuckerman 2007]. The weights considered for these components on average are as follows: physician's work (54%), practice expense (41%), and malpractice expense (5%) [Hetico and Marcinko 2010].

Thus, the "physician work" component accounts for a significant percentage of the total relative value for each service. This component represents the amount of time, technical skills, physical effort, mental effort, and judgment required; they also incorporate the stress experienced by the physician due to potential risk in performing a service for a particular patient [Hsiao et al. 1988]. Clearly, these elements are strongly associated with the "complexity" of medical procedures as we have defined in *Section 3.3* of the article. This can be summarized as follows: When the "complexity" of medical services is higher, the "physician work" is higher, which consequently makes "Medicare allowed amount" higher.

5. 2SLS MODEL OF REPETITIONS DETERRENCE

The main independent variable in the proposed model of repetitions deterrence is endogenous. The reason is that adoption of HIE systems, which generally happens at practice level, depends on features such as rurality, number of physicians who work in a practice, social network measures, and other variables [Yaraghi et al. 2014a]. Since all these variables are not explicitly included in the current analysis, this issue needs to be adjusted in determining the actual effect of HIE on repetitions. We employ 2SLS to apply the Instrument Variable (IV) approach [Riegg 2008] in this context. The IV estimation solves the omitted variable problem by using only part of the variability in the endogenous variable—a part that is uncorrelated with the omitted variables—to estimate the relationship between the endogenous regressor and the dependent variable [Angrist and Krueger 2001]. Given this, the first stage of the proposed model estimates HIE tenure using a set of instrumental variables and control variables. Next, the second stage employs the predicted HIE tenure from the first stage (instead of original values of tenure in HIE) as a focal independent variable along with a set of control variables to predict repetitions of medical services. The two stages of the proposed model are described below.

5.1. Stage 1

Stage 1 estimates HIE tenure for any given practice using practice-specific attributes and network centrality measures. The unit of the analysis in stage 1 is the practice. This is because HIE adoption happens at the practice level and not the individual physician level. In the following, we introduce the instrumental variables to predict tenure in HIE.

Network of Common Physicians

Literature is abundant with evidence on the influence of social networks on innovation diffusion [Valente 1996, 2010]. Centrality is a measure of prestige and criticality of the position of a node in the network [Borgatti and Everett 2006] and is shown to be significant in the resulting behavior in adopting new technologies and innovations [Carrington et al. 2005; Slater et al. 2007]. Different centrality metrics have been designed to measure the extent to which nodes are central in their networks and each of these metrics reflect different concepts and have different interpretations [Freeman 1979].

Degree centrality is the simplest yet the most appealing measure of centrality in social network analysis [Ahuja et al. 2003]. It reflects the number of other nodes that are directly connected to a particular node [Freeman 1979]. We constructed a network of practices where each node represents a practice and a link denotes the number of common providers between a pair of nodes. In this network, degree centrality shows the extent to which practices are sharing providers with others. The practices that share a large number of providers with others will have a high degree of centrality while the peripheral practices with lower degree centrality are the ones which do not have much common providers with others. Nodes with high degree centrality tend to adopt and use a HIE sooner than others. This could potentially be attributed to the levels of communication among practices that are enabled by these cross-sharing providers. The benefits and the value of HIE for a practice that is connected with multiple practices—whether they participate in the system or not—is more significant than the value of HIE for a single practice. In fact, accessing and integrating medical data becomes more complex when physicians work in multiple practices. Therefore, the value and benefits HIE can bring to physicians working in multiple practices is more than the value for other less connected physicians. So we postulate that degree centrality in the network of common physicians is a significant factor in predicting tenure in HIE.

Electronic Prescribing

Electronic prescribing is a way that allows prescribers (doctors or other healthcare providers who are legally allowed to write prescriptions) to send patients' prescriptions electronically and directly to pharmacies. Electronic prescribing makes flow of patients' information more efficient across the continuum of care. To completely realize the value of HIE in the healthcare system, it is essential for pharmacists to involve in exchanging patients' clinical information with physicians. Electronic prescribing facilitates pharmacist participation in HIEs by developing effective and efficient patients' information flow.

Given this, those who already have adopted electronic prescribing can benefit from HIE better. Therefore, we postulate that those who adopt electronic prescribing are more encouraged to adopt HIE than others. In fact, Office of the National Coordinator also employs this association to encourage electronic prescriptions [Banks and Galvez 2012].

Electronic Health Records

EHR is an electronic version of a patient's medical history, which is maintained by the provider over time and may include all the key clinical information pertaining to the patient. HEALTHeLINK provides two channels of access to the patient records: EHR and Virtual Health Records (VHR). If the provider has an EHR that is interfaced to HEALTHeLINK, then the patients' data in the HIE will be automatically delivered and attached to the existing patients' medical records in the HER. However, if such an EHR with a HIE interface does not exist, then the provider can download patients' records through a portal of the HIE called VHR. Clearly, EHR is not required to use the HIE; however, using VHR requires more labor and time in data retrieval. Therefore, given the convenience of EHR, we argue that practices with EHR are encouraged to adopt and use the HIE more than those without it.

In the following, we provide theoretical justification for why we included EHR as an instrument. The EHR systems have been implemented in the U.S healthcare systems with the intention of improving the quality of care through the Meaningful Use program [CMS 2016]. Certainly, these EHR systems bring some benefits to the healthcare systems. However, while almost all of the medical providers in the U.S. have now adopted an EHR system, the intended goals of the Meaningful Use program in terms of reducing repetitions or increasing quality through implementing EHRs have not been fully achieved [HealthAffairs 2015].

To have an impact on reducing the medical repetitions, the mere adoption of EHRs may not be enough. EHRs will have a much larger impact as their usage levels by clinicians increase, yet. this remains a major challenge. Poissant et al. [2005] and Goetz et al. [2012] conducted surveys and interviews with clinicians and administrative staff to examine the level of EHR usage, its benefits, and challenges in small practices. While the interviewees reported increased efficiency as a result of the EHR adoption, they also indicated that there are significant barriers and difficulties in EHR utilization such as lack of knowledge of EHR function. Holroyd-Leduc et al. [2011] systematically reviewed the literature about the impact of the EHR systems to understand the potential benefits and limitations of the EHRs for primary care practices. They found that while EHRs bring structural benefits, the impact on clinical outcomes is not evident. Similarly, Nguyen et al. [2014] conducted a systematic literature review and found a mix of evidence-based positive and negative impacts of EHRs across different evaluation dimensions.

Moreover, there is considerable anecdotal evidence provided by physicians and healthcare providers that, in general, the EHR systems are not as effective as they were expected to be [Campbell 2016]. While EHR is supposed to help physicians, physicians themselves do not believe that it is helping them that much. They believe that EHR is primarily used for billing documentations rather than for medical purposes, which was its original goal. In addition, some members of the U.S Senate Committee on Health, Education, Labor and Pension blasted the EHR systems and claimed that doctors say that EHR systems disrupt workflow and interrupt the doctor-patient relationships and, therefore, that EHR is not worth the effort [HealthcareITNews 2015]. Given the above explanations, we argue that, in practice, the efficiency of EHR is still inconclusive and there is not enough empirical evidence that EHR could reduce the repetition of medical procedures.

Moreover, even if EHR could reduce the repetition of medical procedures, its impact would not be as substantial as the impact of HIE. The main contention of this article is that HIE reduces repetition as it provides physicians comprehensive information about a patient' medical history from all points of care. Having access to this comprehensive source of information enables a physician to avoid unnecessary and redundant tests. On the other hand, the main function of EHRs is to make a patient's information electronically available inside a specific clinical practice. This information is available to the healthcare providers for that practice even without being electronic. In this sense, EHR on its own is very unlikely to reduce repetitions, because it only allows a physician to have access to a patient's medical information that belongs to the same practice. Therefore, while EHRs provides information from the same place, HIE provides the comprehensive medical information of a patient from other points of care as well.

Since we have defined HIE as a count variable, we apply a generalized regression model to predict it. We employ the procedure *Proc Genmod* in Statistical Analysis System (SAS) Software, assuming that the dependent variable is a count variable with a negative binomial distribution $HIE \approx Negbin(hie, k)$. In this distribution, k is the dispersion parameter and hie is the mean of HIE. The stage 1 model is as follows:

$$Log(HIE) = \alpha_1 + \beta_1 NOP + \beta_2 Urb + \beta_3 EHR + \beta_4 PQRS + \beta_5 ERX + \beta_6 Deg\_Cnt + err_1. \quad (1)$$

5.2. Stage 2

Stage 2 predicts the repetition of medical services using the predicted HIE tenure from stage 1 as the focal independent variable and a set of control variables. The unit of the analysis in stage 2 is the physician. In this stage, we only consider those physicians who work in one practice. The dependent variable is the repetition ratio RP_{ij}, which is defined as follows. Consider any medical service j. If j is performed n_1 times by provider i for n_2 patients, then the RP_{ij} for this service is defined as$(n_1 - n_2)/n_1$. The data for this computation are derived from the source MPUP. Based on the discussion in Section 3, the control variable *complexity* is measured by the physician-specific attribute AMA. Besides this, the other control variables are *NOP, Urb, PQR, Exp*, and *gender*. The complete 2SLS model of repetitions deterrence is presented in Figure 2.

Every single physician performs many different types of medical procedures. The repetition of such procedures may in part be affected by the individual characteristics of the physician who performs them. Thus, repetitions of the medical procedures that are all conducted by the same physician are not completely independent from each

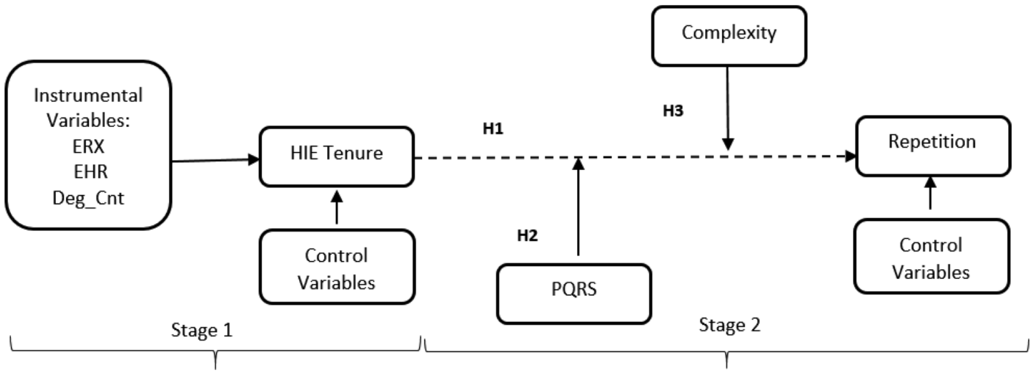

Fig. 2. Structural model of repetitions deterrence (dotted arrow shows that predicted values of HIE tenure is used to predict Repetition).

other and are rather affected by the unobserved characteristics of the same performing physician. This implies that observations are correlated at the physician level, and thus the independency assumption of the classic Ordinary Least Squares (OLS) models is violated. Hierarchical models, also known as multilevel models or nested models, can address problems caused by this situation [Osborne 2000]. For modelling multilevel structured data, hierarchical modelling outperforms classical regression in terms of predictive accuracy [Gelman 2012]. The units of analysis are usually individuals (lower level) who are nested within aggregated units (higher level). Thus, we develop a two-level model, in which medical services are nested within physicians.

The model for testing the hypothesis H1, is given in Equations (2.a.1) and (2.a.2), which represent the procedure level and the provider level, respectively. The provider identifier is $i = 1, \ldots, I$ and the procedure identifier is $j = 1, \ldots J$,

$$\begin{cases} Log\left(0.01 + \dfrac{RP_{ij}}{1 - RP_{ij}}\right) = \alpha_{2i} + \gamma_1 HIE_i + \gamma_2 NOP_i + \gamma_3 Urb_i + \gamma_4 PQRS_i \\ \quad +\gamma_5 EXP_i + \ \gamma_6 gender_i + \gamma_7 complexity_{ij} + err_{ij} & \text{(2.a.1)} \\ \alpha_{2i} = \alpha_2 + u_i & \text{(2.a.2)} \end{cases}$$

By replacing Equation (2.a.2) in Equation (2.a.1), the model can be equally written in the mixed format as Equation (2.a),

$$Log\left(0.01 + \frac{RP_{ij}}{1 - RP_{ij}}\right) = \alpha_2 + \gamma_1 HIE_i + \gamma_2 NOP_i + \gamma_3 Urb_i + \gamma_4 PQRS_i + \gamma_5 EXP_i + \gamma_6 gender_i + \gamma_7 complexity_{ij} + u_i + err_{ij}. \tag{2.a}$$

Next, to test the hypotheses H2 and H3, two interaction terms, "PQRS $\times$ HIE" and "Complexity $\times$ HIE," in addition to other terms are needed. Similarly, the specification of this model is according to Equations (2.b.1) and (2.b.2), which can be equally written as Equation (2.b). In detail, U_i in Equation (2.a) (u'_i in Equation (2.b)) indicates that the intercept varies across the providers. This allows us to consider that the volume of the repetition of the procedures that are performed by the same provider are likely to be similar to each other. We estimate models (2.a) and (2.b) to test our hypotheses,

$$\begin{cases} Log(0.01 + \frac{RP_{ij}}{1-RP_{ij}}) = \alpha'_{2i} + \gamma'_1 HIE_i + \gamma'_2 NOP_i + \gamma'_3 Urb_i + \gamma'_4 PQRS_i + \gamma'_5 EXP_i + \gamma'_6 gender_i \\ \quad + \gamma'_7 complexity_{ij} + \gamma'_8 (complexity_{ij} * HIE_i) + \gamma'_9 (PQRS_i * HIE_i) + err'_{ij} & \text{(2.b.1)} \\ \alpha'_{2i} = \alpha'_2 + u'_i & \text{(2.b.2)} \end{cases}$$

$$Log\left(0.01+\frac{RP_{ij}}{1-RP_{ij}}\right)=\alpha'_2+\gamma'_1 HIE_i+\gamma'_2 NOP_i+\gamma'_3 Urb_i+\gamma'_4 PQRS_i+\gamma'_5 EXP_i$$
$$+\gamma'_6 gender_i+\gamma'_7 complexity_{ij}+\gamma'_8(complexity_{ij}*HIE_i)+\gamma'_9(PQRS_i*HIE_i)+u'_i+err'_{ij}. \quad (2.b)$$

As our models show, the dependent variable RP_{ij} is transformed with a logit function. The reason is that RP_{ij} is a ratio variable, and this violates one of the assumptions of general linear models that the dependent variable is continuous. In regression analyses, data transformation is applied such that the data meet the assumption of the statistical procedure [Nelder and Baker 1972]. In order to get a variable with appropriate range for the proposed method of analysis, we use the Logit function to expand the range of this variable. *Logit* link function transforms our dependent variable to a fairly wide range of both positive and negative values.

6. CLASSIFICATION OF MEDICAL SERVICES

The merging of the CMS datasets HPUP and PC with the HLINK dataset yielded a total of 1,358 medical procedures rendered by the providers in western New York in 2012. While it is theoretically possible to analyze the effect of HIE tenure on repetitions of each procedure individually, four important considerations necessitated a restriction and classification of these procedures as follows.

First, analyzing services individually will yield neither a focused view on the impact of HIE on repetitions of each service (due to limited number of observations for certain services) nor a comprehensive view of the impact in the overall scheme medical services (due to the large number of services). Even though individual service-level analysis is feasible, it will result in a very large array of model results that will create a significant cognitive load and yield little policy and management insights. Therefore, it was necessary to classify medical services into meaningful clusters and analyze the impact of HIE on repetitions at a cluster level that can be both clinically and managerially interpreted with policy implications.

Second, since the objective of this research is to examine the effect of HIE on a physician's decision to repeat a service, it is imperative to consider only those medical services that are ordered and performed by the same physician. In consultation with medical experts, we eliminated a set of services that are recognized as being performed by multiple providers at different facilities. We denote these as Facilities services. For instance, services designated as "Lab Tests" are eliminated, because they are ordered by a physician while performed by another physician at a lab. In addition, we used the location of a service to determine if it is ordered and performed by the same provider.

The medical procedures that are performed in facilities are most often those that have been ordered by other physicians outside of the facility. The performing physician does not have any discretion on whether to perform the ordered procedures. HIE makes a difference at the point on which physicians make a decision about re-ordering a procedure, and, after the decision has been made, HIE will no longer play a role. There are instances in which the ordering and performing doctor are both within the same facility. However, since the Medicare claims data do not distinguish between ordering and performing doctors, we cannot know whether the procedures that are performed in the facility were also ordered in the facility or not. To make sure that our results do not suffer from this limitation, we remove such ambiguous observations from our analysis. We selected only those medical procedures that are ordered and performed by the same physician in the physician's office. We denote these as Office services.

Third, repetitions of not all medical services can be avoided by HIE use; in fact, HIE could have different impacts on the repetitions of different classes of services. To have medically interpretable results, the medical experts classified the procedures into two clusters based on the followings conceptual clinical themes: *Diagnostic* and *Therapeu-*

tic. While these themes are commonly well understood, the following definitions from the Department of Health and Human Services [DHHS 2015] clearly enunciate the difference between them:

> Diagnostic procedures are tests that a doctor uses to help diagnose a person's medical problem or to measure the severity of the problem. The results of diagnostic procedures also help a doctor or other health professional to plan the best course of treatment. For example, Electrographs, a graph made by measuring electrical activity within the body, is a diagnostic test.
>
> Therapeutic procedures are treatments that a doctor or other health professional uses to help, improve, cure or restore function to a person. This may be to repair the effects of injury, disease or congenital malfunctions (birth defects); such as: physical therapies and radiation therapies.

As explained earlier, since we analyze the impact of HIE in the office settings, we expect the HIE adoption to only reduce the repetitions of therapeutic procedures and to not have any effect on the repetition of the diagnostic procedures. A major bulk of the medical data available in the HEALTHeLINK platform pertains to therapeutic procedures. The quantum of data on diagnostic procedures is comparatively limited, because diagnostic data on office-run procedures are rarely pushed to the system by the physicians. Even if the data of previous diagnostic procedures are available on the HIE system, since medical decisions are less time sensitive in the office settings than in the ED settings, physicians prefer to have access to the results of most recent diagnostic procedures and thus they tend to repeat the diagnostic procedures in order to enhance the quality of their medical decisions. This distinction between the type of the medical procedures allows us to conduct a falsification test by examining the impact of HIE on the repetitions of both types of medical procedures. We expect HIE to not only reduce repetitions of therapeutic procedures but also have no effect on the repetition of diagnostic procedures conducted at physician offices.

Fourth, it is necessary to restrict the set of procedures in consideration to only those that were performed by both members and non-members of the HIE for a comparative assessment of the impact of HIE on repetitions deterrence.

Putting it all together, we organized and classified the 1,358 procedures as follows: First, we restricted this set to those performed by both members and non-members of HIE. This resulted in 603 services. Next, the medical experts classified this set into 122 Diagnostic, 149 Therapeutic, and 332 Exclusion procedures. These 332 medical procedures are excluded only because they are being performed by one medical provider as an order of another provider. In our dataset, we can only identify the performing provider of each procedure. For example, consider a primary care physician who orders a blood test that is then performed by a pathologist at a laboratory. Our dataset only identifies the pathologist who performed the test and does not reveal the primary care physician who initially made the decision to order the test. The main objective of the article is to examine the impact of HIE on physicians' decision in redoing medical procedures, and thus, in cases where we do not know about the physician who made the decision to order a procedure, the limitation of our data will not allow us to conduct a meaningful analysis. Because of this data limitation, we consider only those procedures for which the ordering-provider and the performing-provider are the same. An EKG test performed at the physician's office is an example of the procedures that their ordering and performing physicians are the same. The 332 procedures that were excluded are those that we were not sure if their ordering and performing physicians are the same. Thus, removing such services from the analysis does not lead to a selection bias simply because they were not appropriate to be included in the study at the first place. Finally,

Table III. Descriptive Statistics of RP values

Year	2012		2013	
	Diagnostic	Therapeutic	Diagnostic	Therapeutic
Mean of RP (STD)	0.136 (0.203)	0.271 (0.338)	0.120 (0.174)	0.307 (0.345)
Number of observations	2614	3945	2170	3103

Table IV. Descriptive Statistic and Correlation Matrix of Variables Used in the Stage 1 Model

	Mean (STD)	HIE	NOP	Urb	EHR	PQRS	ERX
HIE	3.269 (8.465)						
NOP	8.923 (30.315)	0.000					
Urb	0.829 (0.360)	0.012	−0.048				
EHR	0.368 (0.483)	0.167**	0.178**	0.022			
PQRS	0.407 (0.491)	0.270**	0.180**	−0.006	0.363**		
ERX	0.320 (0.467)	0.231**	0.197**	−0.091**	0.490**	0.435**	
Deg_Cnt	1.452 (4.626)	0.061*	0.794**	−0.040	0.147**	0.192**	0.202**

**: *P*_value <0.01, *: *P*_value: <0.05.

Table V. Descriptive Statistics and Correlation Matrix of Variables Used in Stage 2 (Diagnostic Cluster)

	Mean (STD)	DV	HIE	NOP	PQRS	Urb	EXP	Gender
DV[1]	−2.660 (1.780)							
HIE	5.878 (9.713)	−0.017						
NOP	48.220 (93.499)	−0.066**	−0.104**					
PQRS	0.697 (0.460)	−0.023	0.290**	0.247**				
Urb	0.776 (0.340)	−0.012	−0.004	−0.200**	−0.083**			
EXP	23.676 (10.934)	0.065**	0.098**	−0.006	−0.004	−0.029		
Gender	0.264 (0.441)	−0.154**	−0.019	0.04*	−0.054**	0.062**	−0.304**	
complexity	65.447 (72.635)	−0.038	−0.009	−0.062**	0.029	0.070**	0.018	−0.084**

**: *P_value* <0.01, *: *P_value* <0.05.
1: Transformed Dependent variable in stage 2.

the experts organized the Diagnostic set into 110 Office and 12 Facilities procedures and the Therapeutic set into 97 Office and 52 Facilities procedures. Only the office procedures are considered in this study. The 2SLS models (2.a) and (2.b) have been tested for 2012 and 2013 with the Diagnostic and Therapeutic clusters separately. The total number of observations in each cluster in the respective years 2012 and 2013 are shown in Table III.

7. RESULTS

Descriptive statistic and correlation matrix of variables used in stage 1 and stage 2 model are presented in Tables IV–VI. These values are based on the data of 2012 and the result are similar for 2013. We test for multicollinearity among the independent variables in all the models. This is done by calculating the Variance Inflation Factor (VIF) for all the independent variables excluding the interaction terms. In all the models, the VIF values of all of the predictors are all well below the threshold 5. Thus, multicollinearity should not be an issue [Mason and Perreault Jr 1991; Neter et al. 1989]. To calculate VIFs, we exclude interaction terms following the suggestion of Allison [2012]. Table VII shows the estimation results of the stage 1 model for 2012 and 2013, respectively. The variable PQRS and two of instrumental variables, Deg_Cnt and ERX, are significant in predicting HIE in both 2012 and 2013. The correspondence between the results of the two years shows that 2013 results provide a validity check for those of 2012. Furthermore, 2013 involves more observations than 2012, since the number of HIE participants has increased from 2012 due to new HIE adopters. In this

Table VI. Descriptive Statistics and Correlation Matrix of Variables Used in Stage 2 (Therapeutic Cluster)

	Mean (STD)	DV	HIE	NOP	PQRS	Urb	EXP	Gender
DV	−2.038 (2.610)							
HIE	5.732 (10.101)	−0.207**						
NOP	58.959 (108.646)	−0.190**	−0.136**					
PQRS	0.712 (0.453)	−0.238**	0.332**	0.285**				
Urb	0.753 (0.354)	0.060**	0.019	−0.220**	−0.050**			
EXP	22.353 (10.900)	−0.108**	0.121**	−0.004	−0.003	0.022		
Gender	0.322 (0.487)	−0.047**	−0.003	0.065**	0.010	−0.038*	−0.300**	
complexity	43.234 (89.044)	0.072**	−0.041**	−0.052**	−0.023**	0.064**	0.022**	−0.070**

**: *P_value* <0.01, *: *P_value* <0.05.

Table VII. Maximum Likelihood Parameter Estimates of Stage 1

Parameter	**Estimate (STD), 2012**	**Estimate (STD), 2013**
Intercept	−0.003 (0.370)	0.586 (0.364)
NOP	−0.036* (0.015)	−0.036* (0.015)
Urb	0.095 (0.376)	0.082 (0.367)
EHR	0.156 (0.339)	0.124 (0.325)
PQRS	1.220** (0.314)	1.162** (0.302)
ERX	0.661* (0.338)	0.715* (0.323)
Deg_Cnt	0.181* (0.079)	0.168* (0.077)
Dispersion parameter	17.760 (1.553)	17.298 (1.385)
Pearson chi-square (Value/Df)[1]	0.732	0.571
Number of observations	1051	1066

**: *P*_value <0.01, *: *P*_value: <0.05.
1: The model fits reasonably well when the goodness-of-fit chi-squared test is not statistically significant.

context, it is also important to recognize that those who participated in HIE in 2012 would have become more adept in using HIE in 2013. In sum, the 2013 results yield a robustness check for the model.

Sargan's test checks the validity of our assumption that instrumental variables that are excluded from the main regression are uncorrelated with the residuals. The Sargan's test statistic is $N \times R^2$, where N is the number of observations and R^2 is the coefficient of determination from the OLS regression of the residuals onto the set of all variables (independent variable, control variables, and instrumental variables) except the endogenous one. Under the null hypothesis, R^2 should be very small. The statistic $N \times R^2$ will be asymptotically chi-squared with K degrees of freedom, where K is the number of endogenous variables minus the number of instrumental variables. Rejection of the null hypothesis indicates that at least one of the instruments is not valid.

We performed Sargan's test. Our results show that R^2 is very small ($\sim$0.001). This implies that the instrumental variables cannot adequately explain the residuals, and thus instrumental variables are not correlated with the residuals. However, as N is a large number, the test statistic $N \times R^2$ also becomes a large number ($0.01 \times 3921 = 39.21$), which leads to rejection of the null. However, prior literature mentions that the test will have a very high probability of false rejection as the number of the observations increases [Westgard et al. 1977]. The critical value for the chi-square (df = 2, alpha = 0.05) equals 5.991. If $N \times R^2$ is larger than the critical value 5.991, then the null hypothesis will be rejected. In our case, the null hypothesis will be rejected if $N \times R^2 \succ$

Table VIII. Estimation Results of Stage 2 for the Year 2012

	Model (2.a) Estimation (Standard Error)		**Model (2.b) Estimation (Standard Error)**	
Effect	Diagnostic	Therapeutic	Diagnostic	Therapeutic
Intercept	−2.555** (0.118)	−0.144 (0.112)	−2.537** (0.191)	1.801** (0.165)
Exp	0.004 (0.003)	−0.029** (0.003)	0.004 (0.003)	−0.027** (0.003)
Gender	−0.583** (0.062)	−0.488** (0.065)	−0.586** (0.062)	−0.447** (0.063)
NOP	−0.001* (0.000)	−0.005** (0.000)	−0.001* (0.000)	−0.005** (0.000)
Urb	0.012 (0.082)	0.132 (0.087)	0.013 (0.082)	0.085 (0.085)
PQRS	0.055 (0.065)	−0.456** (0.074)	0.033 (0.162)	−2.428** (0.159)
HIE	−0.009** (0.003)	−0.070** (0.004)	−0.018 (0.112)	−1.543** (0.112)
Complexity	−0.002** (0.000)	−0.001** (0.000)	−0.002** (0.000)	−0.002** (0.000)
HIE×Complexity	–	–	0.000 (0.000)	0.000 (0.000)
HIE×PQRS	–	–	0.010 (0.112)	1.472** (0.112)
physician level R^2	0.052	0.141	0.053	0.189
Service level R^2	0.017	0.015	0.017	0.013
Number of observations	2604	3921	2604	3921

**: *P*_value <0.01, *: *P*_value <0.05.

$Chi - Square(\mathrm{df} = 2 \text{ and alpha} = 0.05) \xrightarrow{yields} 3921 \times R^2 \succ 5.991 \xrightarrow{yields} R^2 \succ 0.0015$. Thus, with sample size, $n = 3921$, as long as R^2 is larger than $0.\mathit{0015}$, the null hypothesis would be still rejected. Since the initial $R^2$is extremely small, we believe that Sergan's test does not produce favorable results only because we have a very large sample and not because of s poor choice of IV. In other words, as described in the prior literature, in our context, due to the large sample size, Sargan's test leads to a false positive.

The stage 2 analysis has been carried out as follows. We had 2 years of data [2012, 2013], two clusters of medical services (Diagnostic, Therapeutic), and two estimation models (Equations (2.a) and (2.b)). This yields eight combinations of (year, cluster, model). The complete set of results is summarized in Tables VIII and IX. Note that as in stage 1, the stage 2 analysis for 2013 is used as a validity and robustness check for the results obtained from 2012. The models fits reasonably well, because the goodness-of-fit likelihood ratio test are statistically significant. Similarly to R^2 in single level regression, physician level R^2 and service level R^2 represent the explained variance by the explanatory variables in each level [Raudenbush and Bryk 1986].

Some key observations on the clinical and statistical differences between the Diagnostic and Therapeutic clusters are as follows. A major bulk of the medical data available in the HEALTHeLINK platform pertains to therapeutic procedures, since they are pushed to the HIE by the large hospitals. The quantum of data on diagnostic procedures is comparatively limited. The result of diagnostic medical procedures performed in the office settings are rarely pushed by the physicians. Furthermore, diagnostic procedures are done less often than therapeutic procedures. While diagnostics capture medical conditions at specific points of time, therapeutic data pertain to a continuum of care and hence are more frequent. This is confirmed in the mean RP values in the two clusters in both 2012 and 2013 as shown in Table III. The mean RP of the Therapeutic cluster is significantly larger than that of the Diagnostic cluster in both years (the *t*-value is 18.22 for 2012 and 23.34 for 2013). Consequently, we do not expect HIE to significantly impact repetitions in the Diagnostic cluster, while it could be significant in the Therapeutic cluster.

We ran model (2.a) to test the hypothesis H1. The results show a negative significant effect of HIE in the Therapeutic cluster in both 2012 and 2013, which supports

Table IX. Estimation Results of Stage 2 for the Year 2013

	Model (2.a) Estimation (Standard Error)		**Model (2.b) Estimation (Standard Error)**	
Effect	Diagnostic	Therapeutic	Diagnostic	Therapeutic
Intercept	−2.494** (0.122)	0.066 (0.129)	−2.532** (0.187)	1.649**(0.185)
Exp	−0.004 (0.003)	−0.027** (0.003)	−0.003 (0.003)	−0.025** (0.003)
Gender	−0.523** (0.069)	−0.450** (0.073)	−0.520** (0.070)	−0.408** (0.072)
NOP	−0.001 (0.001)	−0.004** (0.000)	−0.001* (0.000)	−0.005** (0.000)
Urb	−0.040 (0.090)	0.160 (0.099)	−0.042 (0.089)	0.115 (0.098)
PQRS	0.009 (0.066)	−0.353* (0.085)	0.046 (0.148)	−1.986**(0.170)
HIE	−0.002 (0.002)	−0.058** (0.004)	0.008 (0.053)	−0.746** (0.062)
Complexity	−0.001 (0.000)	−0.002** (0.000)	0.000 (0.000)	−0.002** (0.000)
HIE×Complexity	–	–	0.000 (0.000)	0.000 (0.000)
HIE×PQRS	–	–	−0.010 (0.053)	0.691** (0.062)
physician level R^2	0.050	0.128	0.055	0.163
Service level R^2	0.003	0.022	0.002	0.021
Number of observations	2163	3083	2163	3083

**: P_value <0.01, *: P_value <0.05.

H1 with a robustness check. This implies that HIE leads a physician to avoid redoing a therapeutic medical procedure that has been previously done for a patient by the same physician. This result shows that, during therapeutic care, physicians tend to use the prior medical information on the patients that are available through HIE before deciding on performing such procedures. In the continuum of therapeutic care where certain procedures are performed multiple times on a patient, HIE could have a significant impact on reducing unnecessary repetitions. However, no significant effect of HIE on repetition is observed in the in Diagnostic cluster in both the years (except model (2.a) for year 2012). These findings confirm the falsification test developed in the previous section. As observed earlier, the diagnostic procedures being less frequent than therapeutic procedures and the fact that many physicians may not push the diagnostic results to the HIE together imply that HIE does not have a significant impact on repetitions of diagnostic procedures. This result is also consistent with the descriptive statistics reported in Table III. In addition, both PQRS and Complexity seem to have significant negative effects on repetitions in the Therapeutic cluster in both 2012 and 2013. For example, the coefficient −0.456 for variable PQRS in the year of 2012, indicates that while other independent variables in Equation (2.a) are fixed at their average level, $\log(0.01 + \frac{RP}{1-RP})$, for physicians who participate in PQRS on average is 0.456 less than $\log(0.01+\frac{RP}{1-RP})$ for physicians who do not participate in PQRS. Suppose that the RP of medical service A provided by a physician who does not participate RP in PQRS is 0.7. If the physician participates in PQRS, assuming other variables are fixed at their average level, then the ratio of repetition will become 0.59. That is, the ratio of repetition decreases by 0.11 units which is a considerable amount. Similarly, coefficient −0.001 for variable complexity in the year 2012 indicates that while other independent variables are fixed at their average level, one unit increase in the complexity leads to 0.001 units decrease in the logit of dependent variable: $\log(0.01 + \frac{RP}{1-RP})$. Because the dependent variable, RP, is a ratio variable (ratio of repetition), this amount of change in the logit function leads to an economically significant change in RP. These variables do not seem to have any significant impact in the Diagnostic cluster, although complexity is significant only in 2012. A detailed study of these factors is interesting but is recommended for future research, since it is beyond our current scope.

Next, we ran model (2.b) to test hypotheses H2 and H3. The results support hypothesis H2 in the Therapeutic cluster in both 2012 and 2013. Actually, the significant effect of interaction term "PQRS × HIE" in model (2.b) shows that the effect of HIE on repetition is conditioned on PQRS. The positive sign of this interaction term shows that HIE impact is lower for PQRS participants than non-participants. As discussed earlier, a primary reason for this could be that PQRS participants are already so cautious and quality sensitive that HIE cannot contribute to a notable decrease in the repetitions. Hypothesis H2 is not supported in the Diagnostic cluster in either year. The same reasoning with diagnostics as in H1 would apply in this observation. We note that using the variable "length of participation in the PQRS" instead of the binary variable "participation in PQRS" could enable us to get a better insight about the impact of this program. However, we could not include in the study due to the limitation in our datasets.

Our results do not support hypothesis H3 in both clusters in each year, as the effect of interaction term "complexity × HIE" is not significant. Although complexity seems to be independently significant in impacting repetitions, it does not seem to have a moderating effect on the influence of HIE on repetitions. One explanation is that a complex procedure could lead a physician to avoiding repetitions as much as possible due to the inherent complexity of the procedure itself, regardless of whether HIE is available. The medical experts in this study indicated that during a patient's care, instead of redoing a complex procedure, a physician could choose a simpler procedure to perform or seek prior medical information on the patient through other sources. This could decrease the volume of complex procedures to an extent that HIE may not have a perceivable impact on their possible repetitions.

To strengthen our causal inferences from the cross-sectional analysis, we use our data to conduct an additional analysis. We employ Equations (2.a) and (2.b) for each cluster using the dependent variable of the year 2013 and independent variables of the year 2012. The results of these models are consistent with the results obtained from cross-sectional analysis of the years 2012 and 2013 and thus support our main findings.

We note that the standard errors reported in Tables VIII and IX are adjusted standard errors obtained by the bootstrapping approach. The standard errors of parameter estimators in the second stage should be adjusted as we have inserted predicted values of a variable instead of the original values. In fact, because the second stage will yield the "wrong" residuals (being computed from the instruments rather than the original variables), all statistics computed from those residuals will be incorrect [Wooldridge 2012]. The standard errors of coefficients are incorrect, because they are computed using wrong residuals.

Bootstrapping is a non-parametric approach for estimating properties (such as variance) of an estimator by generating a number of samples with replacement of the observed dataset and measuring that estimator (an estimator can be a coefficient in a regression model). Bootstrapping can be used for hypothesis testing. It is often used as an alternative to statistical inferences where the assumption of parametric models is in doubt or where parametric inferences require complicated formulas for the calculation of standard errors [Mooney et al. 1993].

To find the standard errors of the coefficients of our second stage, we have applied a bootstrapping approach to each model as follows: We first used *proc surveyselect* in SAS to generate 1,000 samples of the observations [UCLA 2016]. We replicated the second-stage model for each sample and saved the coefficients estimated by the model for each sample. For each coefficient, we therefore had 1,000 estimated values. We then used these 1,000 estimated values to compute the mean and the standard deviation for each of the corresponding coefficients.

8. DISCUSSION AND CONCLUSIONS

Repetitions of medical services by providers have often been cited as major sources of costs by both policymakers and academic researchers. Such repetitions could occur due several reasons, including missing information on past performance, complex EMR systems, providers' lack of experience, medical necessity, and financially motivation. Prior studies have shown that missing previous medical information of patients during the time of care is an important reason. The federal healthcare initiatives and legislation have mandated HIEs to address the missing information problem, while quality-reporting programs tend to curb the repetitions due to inappropriate use of medical services or financially motivated reasons.

Our key findings suggest that HIE helps to reduce repetition of therapeutic medical procedures but does not seem to impact diagnostic procedures. Further, we found evidence that the impact of HIE on repetition is more efficient for those who do not participate in the PQRS program. However, our results did not reveal that the level of complexity of medical procedures makes the impact of HIE stronger. A limitation of this study is that we did not have access to patients' data. To protect the privacy of patients, CMS does not provide the patient-level information, and thus it was not possible to evaluate whether a repeated procedure is medically necessary. Moreover, our findings mainly are based on cross-sectional analysis, which is limited in its ability to make causal inferences. In addition, our results would have been improved if we had access to measures of actual HIE use rather than adoption. Focused studies that incorporate these patient-level and HIE usage-level data will shed considerable further light in this direction and are suggested for future research.

In this article, we have addressed some of the important shortcomings of prior studies that have shown HIE reduces repetition of medical procedures. The main theoretical and practical findings of our study are summarized as follows: First, most of the prior studies have looked at medical procedures performed in ED settings. However, we study the impact of HIE in a new clinical setting: the office of the physicians. This is important and in the particular interest of health policymakers, as the difference in the setting in which HIE is being used could lead to different outcomes. The medical encounters in physician's offices are usually scheduled and thus non-urgent, which makes the likelihood of repetition higher. To our knowledge, this is among the first studies that provide evidence for the effectiveness of HIE usage in the office settings. In addition, by separate analyzing of diagnostic and therapeutic medical procedures, we have also shown that the HIE does not impact different types of medical procedures in the same way. Second, our findings are more robust as we examine overall HIE impact on a larger number of medical procedures. Previous studies are not statistically robust enough as they look at a limited set of services. Our findings thus reveal the larger scope of HIE benefits in addressing the problem of unnecessary utilization of medical services. Finally, prior research has not examined factors that could enhance or impede the possible benefits of the HIE systems. We study how the impact of HIE can be moderated by physician participation in quality reporting programs. Our findings inform health policymakers that concurrent participation of physicians in different initiative programs may impact the expected specific outcome of each program and thus subsequent healthcare outcomes.

This article builds on the existing literature on HIE participation and contributes to the theory by identifying the processes through which HIE participation leads to medical outcomes. While the literature provides substantive knowledge about the antecedents of HIE participation, the consequences of HIE participation have not been fully examined, especially when it comes to the outcomes of HIE participation in physician offices and medical practices. To the best of our knowledge, prior studies on the outcomes of HIE participation were limited to EDs, and therefore our understanding of the outcomes of HIE participation in other settings including physicians' offices and medical practices was very limited. Our article bridges this gap in the literature and contributes to the theory by building and testing a set of hypotheses on the benefits of HIE participation on repetition of therapeutic and diagnostic medical procedures at the physicians' offices.

Our current research aims to assess the extent of repetitions avoided by federal initiatives such as HIE in the Affordable Care Act and other programs such as PQRS using publicly available CMS data and other data sources. As a result, we expect the findings of this research to confirm the efficacies of these programs and lead to specific guidelines for policymakers in the government to regulate and streamline these initiatives for enhanced achievement of their objectives in the future. Furthermore, this research also reveals the effectiveness of HIEs in decreasing healthcare costs and improving the quality of care. As a consequence, this is expected to lead to improved information and data management at HIEs and extended scope and reach of their services to members, leading to sustainable HIE business models, which seem to be in their infancy at this time. Finally, financially incentivized procedural repetitions have been a well-recognized problem. While this research is exploratory, it is expected to shed considerable light on our understanding of this problem by statistically assessing the influence of control mechanisms such as PQRS on procedural repetitions. This is expected to open up a significant new avenue of research on healthcare ethics, laws, and technologies. To our knowledge, this research is probably the first effort at addressing in a concurrent and integrative manner the separate but related issues of better medical care at lower costs with the help of HIEs and quality assurance programs, which is expected to lead to sustainable HIE business models.

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