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Examining the theoretical mechanisms underlying health information exchange impact on healthcare outcomes: A physician agency perspective

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Direct and Spillover Effects of Patient Access to Health Information Exchange on Medical Costs: A Natural Experiment

Completed Research Paper

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Introduction

Fragmented patient care and resultant data fragmentation across disparate healthcare providers drive up medical costs. Thus, there is a rising interest in developing patient-centered health information technology (HIT) that offers the promise of connecting patients and healthcare providers to patients' health data from multiple sources. Despite progress, there exist disparities in patient access to patient-centered HIT. A recent report of more than 1100 healthcare consumers shows that 31 percent cannot easily obtain their medical records from their healthcare provider which prevents them from sharing data with another provider (Health 2017). Patient access to patient-centered HIT is fundamental as it enables collection and sharing of the patient's data so that healthcare providers could provide better care, improve efficiency and thereby lower medical costs. In this study, we focus on health information exchange[1] (HIE), a distinct patient-centered HIT which facilitates capturing, storing, sharing, and retrieval of patient health information of medical providers across organizational boundaries (Ayabakan et al. 2017), and we define patient access to HIE as the capability of the patient and health providers to appropriately access and securely share the patient's health data via HIE. Despite the numerous efforts to improve patient access to HIE, it is unclear whether and how patient access to HIE could lead to a reduction in medical costs.

The literature on digital divide has offered valuable insights on the consequences of the divide in access to ICT (e.g., computers and Internet), such as inequality of learning outcomes arising from the divide in student digital access (Wei et al. 2011). It is noteworthy that patient access to HIE is very different from user access to ICT examined in prior studies because the use of HIE involves two types of end users—both patients and healthcare professionals who act as agents of patients. When there are costs to the physician associated with the use of HIE, physician agency would become an unneglectable issue in understanding how medical costs would be affected. Combining the theory of information sharing and physician agency, we identify two aspects of the impact of access to HIE on medical costs in the inpatient setting. On one hand, based on the theory of information sharing, we argue that patient access to HIE could directly lead to lower

[1] "health information exchange" stands for both the verb denoting sharing of information and the noun denoting the technology of which the governance and technical structures enable information sharing in a secure and reliable way.

test costs of a hospitalization episode by curtailing unnecessary medical testing (Ayabakan et al. 2017). On the other hand, access to HIE can create spillover effects at the department level. We argue that income loss and efficiency improvement of a hospital department could create a link between a patient's access to HIE and the medication costs of another patient. From the perspective of physicians whose incomes are linked to their department revenue, the reduction in test costs for patients with access to HIE would mean a loss of department revenue and thus individual physicians' income (Agarwal et al. 2010). The income effect hypothesis suggests that physicians acting as patients' agents would have the ability and desire to induce demand in response to negative income shock (McGuire 2000). As the information asymmetry regarding the demand for prescription medications is particularly great (Lundin 2000), one would expect that physicians would compensate for the income loss by inducing more medication demand. Thus, the medication costs of hospitalization episodes would be increased due to the spillovers from access to HIE of other patients in the same department. Nevertheless, income loss could be mitigated by increasing the number of admissions as it is another important contributor to a department's revenue (Handel et al. 2010). The potential of increase in the number of admissions could be realized if departments capitalize on the HIE to improve technical efficiency (i.e., increasing the number of discharges given fixed inputs), which in turn leads to enhanced capacity to accommodate more demand. We argue that compared to low-demand departments, high-demand departments that have more unmet inpatient demand are more likely to turn increased capacity into more admissions of new patients and thus gain financial benefits. Therefore, one would expect a "within-department" spillover effect on medication costs from access to HIE of other patients, which would be less salient for high-demand departments though.

The Chinese healthcare system provides a compelling context to explore these questions because the government has taken a number of initiatives for HIE development, but there is still a gap in access to HIE across different patient groups. Our goal in this research is to investigate the direct and spillover effects of access to HIE on the medical costs of a hospitalization episode. To this end, we examine the impact of a regional HIE in China which was accessible to only a specific patient group, and we exploit the HIE implementation as a natural experiment. We leverage discharge data from a participating hospital to compare the medical costs between patients with access and patients without access to the HIE. We employ propensity score matching and difference-in-difference to estimate the direct effects of access to HIE on test costs. To investigate the spillover effects, we exploit the variation in the percentage of patients with access to HIE in a department. We find that access to HIE has a negative effect on test costs, and it has spillover effects on medication costs for low-demand departments. We further show that the spillover effects are linked to income loss and efficiency improvement of a department. To assess the income-loss mechanism, we investigate the changes in the test revenues of a department related to the percentage of patients with access to HIE. Furthermore, the efficiency-improvement mechanism is validated by testing the changes in the number of admissions of a department and length of stay of a hospitalization.

This study makes contributions to several streams of literature. First, prior research investigating the impact of HIE has focused on either test costs or overall medical costs. Although HIEs are found to have negative effects on test costs, HIE impact on overall medical costs is inconclusive. HIEs are found to reduce medical costs in some hospitals (Frisse and Holmes 2007; Frisse et al. 2012; Tzeel et al. 2011), but not in some others (Bailey et al. 2013; Lang et al. 2006). We give an in-depth examination of the HIE impact on different medical costs. Specifically, we propose differential and even contrasting effects of HIEs on test costs and medication costs—test costs of a hospitalization episode would be directly reduced while medication costs could be increased through spillover effects. Additionally, we extend the literature on evaluation of HIT investments. Prior research in this stream of literature has adopted either a production view or a process view. Studies adopting a production view use production function or stochastic frontier analysis to analyze the impact of HIT investments on cost reduction at an aggregate level (Menon et al. 2000; Menon et al. 2009). In contrast, studies adopting process view examine how HIT could reduce costs associated with utilization of services through improvement in the care process such as improvement in adherence to recommended care and reduction in medication error at a granular level (Bates et al. 1997; Teich et al. 2000). In this research, we consider both aggregate- and granular-level (i.e., department- and hospitalization-level) mechanisms. Moreover, we highlight the income-loss and efficiency-improvement mechanisms at the department level that drive the spillover effects. Lastly, this study contributes to the literature on physician agency by investigating the role of physicians in achieving effective cost control.

Background

Waste and Inefficiency in Healthcare

Per capita inpatient expenditure in public hospital has risen significantly in recent years in China, from CNY 6194 in 2010 to CNY 8890 in 2017. Furthermore, diagnostic test expenditure and medication/drug expenditure accounted for as high as 7.1% and 43.1% of total inpatient expenditure in 2010, and 8.9% and 31.3% in 2017 (See Chinese Health Statistics Yearbook 2018).

The fragmented nature of the health care system is one critical reason for the unnecessary healthcare services which drives the increasing medical costs. Primary health care in China is weak and its core function in gatekeeping or care-coordination is not met (Yip and Hsiao 2014). This makes the healthcare system in China even more fragmented and hospital-centric, with public hospitals delivering approximately 90% of the inpatient and outpatient care (Yip and Hsiao 2014). A typical patient receives diagnosis and treatment from different hospitals which usually use disparate information systems to digitalize, process and store patient data. The fragmented healthcare delivery and unstandardized patient data result in siloed patient medical information (Miller and Tucker 2014). The lack of interoperability between information systems across hospitals creates significant technical barriers to retrieving patient data directly from other hospitals (Ayabakan et al. 2017). For this reason, physicians rely on paper-based medical records or the patient's self-report for obtaining patient data, and the data obtained is usually not completely accurate or interpretable. In such situations, physicians tend to repeat diagnostic tests and/or prescribe redundant medications to improve diagnosis and treatment outcomes.

The profit-driven behavior and its resulting excessive use of diagnostic tests and medication have been recognized as influential factors of the drastic increase in hospitalization expenditures (Liu et al. 2000). Under the fee-for-service payment method, healthcare providers are paid for the quantity of care. There is little motivation for healthcare providers to reduce medical expenditures for their patients or the insurance provider. Public hospitals in China are self-financing entities as they are responsible for their own profit and loss. While public hospitals receive government subsidies, health services charges account for approximately 90% of their revenues (Yip and Hsiao 2014). With fee-for-service still the dominant payment mechanism for hospitals, hospitals encourage physicians to prescribe drugs and tests that are not clinically needed. Furthermore, starting in 2006, hospitals are allowed to set a 15% markup on drug sales, which makes drug sales an important revenue source for hospitals (Liu et al. 2000). In order to achieve the financial goal of the hospitals, physicians have been paid a bonus since the 1980s; typically, each department of a hospital is given a revenue target, and the department can use the residual income to pay bonuses for the physicians (Liu et al. 2000). Given that the government sets physicians' basic salaries at a very low level, physicians have strong incentives to enlarge their income by gaining bonuses through their services to patients. A survey in 2007 suggests that many physicians felt compelled to earn or to supplement their livelihood through the sale of drugs or the performance of diagnostic tests (Fan 2007).

Policies Addressing Waste and Inefficiency

The Ministry of Health of China has taken persistent efforts to build a care delivery system that is cost effective and of better quality to respond to the population needs. Among the numerous early attempts to address waste and inefficiency, some yielded modest success while others aggravated the problem. For example, the government set artificially low prices for outpatient visits, essential medicine, and standard diagnostic tests. However, in response to the restrictions, hospitals increased their supply of services not covered by restrictions, such as prescribing longer hospital stays and more expensive diagnosis and medicine (Liu et al. 2000). Though regulations could curb providers' aberrant behavior in the short term, providers have ingenious ways of getting around regulations in place due to the pervasive information asymmetries in the sector. Besides, third-party payers may have neither capacity nor incentives to control the behavior of health care providers. Physician payment reform is an alternative strategy for alleviating inefficiency. Indeed, it has shown promising results. For example, average expenditure per admission fell below the level at fee-for-service hospitals after Hainan province implemented prospective payment at six key hospitals in 1997 (Yip and Eggleston 2004). However, it also creates new concerns such as underuse of needed services (Becher and Chassin 2001).

The ongoing national health reform in China has also facilitated many HIE projects. Most of the HIE projects are financed and owned by the government, and public hospitals are the main participating entities. A governance model will be set up for the HIE project to develop the relevant policy and agreement to assure compliance. At a technical level, HIEs increase interoperability by facilitating the use of the same standards and supporting the automated transmission of patient data in a secure manner. The data architecture of HIEs could be a centralized model where all patient data is uploaded to a central data repository, a distributed model where each hospital maintains the patient data and exchanges patient data through HIE, or a hybrid model containing elements of both. Unlike price regulations or physician payment reform, HIEs do not involve substantial changes in governance and incentive structures. It is important to understand, in such a situation, whether and how HIE could help reduce waste and inefficiency, so as to control medical costs.

Related Literature and Hypotheses Development

Redundant Tests and Health Information Sharing

The fragmented healthcare delivery has been recognized as one important driver for unnecessary tests (Miller and Tucker 2014). Patients often seek health services from multiple healthcare providers, and this would generate redundancy of medical tests (Ayabakan et al. 2017). Prior studies often view a test as redundant if a test of the same type had previously been ordered within its test-specific interval (Bates et al. 1998). The redundancy of diagnostic tests is pervasive in the inpatient setting where patients tend to have complex conditions and need a series of diagnostic tests. Prior study has shown that at least 8.6% of a defined group of commonly performed tests in the inpatient setting are redundant (Bates et al. 1998).

Patient access to HIE denotes that his/her medical information is stored in a standardized format and could be shared securely across healthcare providers via HIE. Medical information such as previous medications, laboratory test reports, radiology images, and allergies which were previously unavailable could be easily accessed by the physician when the patient is admitted. Compared with the conventional ways of hospitals sharing health information—through paper-based reports or patient self-report, HIEs provide a more convenient way for physicians to retrieve comprehensive and accurate patient's medical information. The availability of accurate and complete information could foster effective communications between patients and physicians and help physicians to better understand the patient's medical history (Frisse 2010). HIEs not only increase interoperability of patient data but also facilitate trusted exchange among participating hospitals. It reduces the information sharing barriers associated with liability risks of acknowledging tests done in other hospitals. Thus, physicians could avoid carrying out redundant diagnostic tests for the patient who has access to HIE without diminishing the quality of diagnosis and medical decisions.

As test ordering is controlled by physicians, the realization of such benefits hinges on physician behavior. Given the burden of increasing patient intake with limited beds, we argue that physicians have the motivation to utilize easy access to patient information to save time and achieve expedited care delivery. Furthermore, access to HIE also equips the patient with information that could facilitate better communication with the physician. With copayment, one would expect that patients still have the motivation to avoid repeated testing to reduce medical expenditure. The patient would exert more influence on constraining the physician's test-ordering behavior. The patient may remind the physician of the available data of good quality in HIEs or insist on using the test results of previous tests. Redundant tests which would have been carried out for the reason of the physician's defensive practice or financial incentives could be avoided due to the pressure from the patient. Overall, patient access to HIE gives the physician both opportunity and pressure to reduce redundant testing. Therefore, we hypothesize that

H1: The test costs of a hospitalization episode will be reduced if the patient has access to HIE.

Physician Agency and Income Effect

While HIEs could cause a reduction in the test costs of a hospitalization episode on one hand, on the other hand, it also means a loss in the revenues of the department (Walker et al. 2005). The individual physicians' incomes which are tied with the department revenues would also be negatively affected. Physicians acting as the agent of patients may take undesirable reactions to the loss of incomes. In the field of health economics, it is well recognized that the professional relationship builds on the information gap between physician and patient, and permits the physician to decide the demand. Prior research has adopted the concept of physician-induced demand to explain and predict physician behavior. A precise definition of physician-induced demand is provided as follows:

"Physician-induced demand exists when the physician influences a patient's demand for care against the physician's interpretation of the best interests of the patient" (McGuire 2000).

The main assumption of physician-induced demand is asymmetric information between the physician and the patient, and, in the case of third-party financing the medical care, between physician and the insurance provider (Evans 1974). Ideally, physicians should supply services based on medical evaluation, and social and patient costs, without regard to their private economic interests; physicians act as "double agents" to achieve efficiency in service provision (Lundin 2000). Nevertheless, because the patient is poorly informed and/or the insurance providers do not have a perfect evaluation of physician's service, the physician has the opportunity to influence the amount of healthcare service to maximize his/her own interest (McGuire 2000). Because many of the characteristics of patients and physicians that determine the appropriate amount of service are unobserved, it is impossible for researchers to determine whether a physician induces demand with regard to their own economic interests. A large body of literature has adopted alternative strategies to identify physician-induced demand. Particularly, many studies test for induced demand by using an exogenous shock to physician's incomes (McGuire 2000). Prior studies have found that the reduction in physician fees, especially Medicare fee changes in the U.S. increased treatment intensity (Earle 2013; Gruber et al. 1999; Yip 1998), and within-state fertility declines led to within-state increases in highly reimbursed caesarean delivery in lieu of normal childbirth (Gruber and Owings 1996). Altogether, these evidences support the income effect hypothesis that physicians respond to a potential loss of incomes by increasing demand (McGuire and Pauly 1991).

In our context, we contend that the income effect would dominate the physician behavior because of high financial pressures faced by physicians. The more patients having access to HIE, the more loss of the department revenue would incur. In the situation where individual physicians' incomes are tied with the department revenues, the department-specific shock would motivate the physicians to use more services. In the literature of health economics, demand inducement for medicine has long been a matter of concern because deciding appropriate amount and types of medicine involves much information asymmetry, and thus medicine demand is pervasively distorted (Lundin 2000). Moreover, the fee-for-service payment scheme, coupled with policy-permitted markup of medicine sales, further incentivizes physicians to induce demand for medication to achieve their desired incomes. Though HIEs make the prescription information more transparent between providers, lack of perfect methods to evaluate the appropriateness of medicine demand makes it difficult to regulate the physicians' prescription behavior. Thus, one would expect a negative "within-department" spillover effect of access to HIE. Specifically, the more the percentage of patients having access to HIE in a department, the more loss of incomes would incur, resulting in more medicine demand for the patients in the same department. We therefore hypothesize that

H2a: The medication costs of a hospitalization episode will be positively associated with the percentage of patients having access to HIE in the department.

We have argued that physicians could increase medication costs for each patient to compensate for the income loss. Alternatively, physicians could capitalize on the use of HIE to increase technical efficiency (i.e., increasing the number of discharges given a fixed number of professionals and beds) and admit more patients. Indeed, physicians would have a strong motivation to take the latter approach to maximize their incomes because even under the fee-for-service payment, there is a reimburment ceiling (i.e,. maximum reimbursement amount per capita) specified by the medical insurance schemes in China.

There have been abundant evidence in the literature showing that investments in HIT could improve technical efficiency (i.e., increasing the number of patients processed) (Watcharasriroj and Tang 2004). In our context, HIEs offer the opportunities to improve technical efficiency mainly through shortening length of stay. Timeliness is one of the benefits of using HIE. Time spent by the hospital staff in verifying information could be reduced, which includes that of medical tests, results and diagnoses of patients (Blaya et al. 2010). Moreover, the comprehensive and accurate information including previous medicine list and allergies offered by HIEs could largely reduce drug interactions and other adverse drug events. Therefore, healthcare is safer by using HIE, and it helps to reduce inpatient length of stay (Kaelber and Bates 2007).

Additionally, the increase in technical efficiency would be more financially beneficial for high-demand departments in which insufficient capacity to effectively meet inpatient demand is a key bottleneck constraining their revenues. Improved efficiency could help the high-demand departments to free up beds for new patients and accommodate more demand that was previously unmet. As a consequence, the reduction in test costs would be less likely a concern to the high-demand departments as they can admit more new patients. The negative externality of access to HIE would be less salient for the high-demand departments. Therefore, we hypothesize that

H2b: The positive effect of the percentage of patients having access to HIE in the department on the medication costs of a hospitalization episode will be stronger for low-demand departments than high-demand departments.

Research Method

Research Context

Our research context is a tertiary public hospital (hereinafter referred to as the focal hospital) in China which participated in a city-wide HIE. The HIE was funded by the local government institution, and there were in total 23 public hospitals participating in the HIE project. The implementation of HIE in the focal hospital began in March 2008, and it was officially put into use in April 2008. Along with the HIE implementation, the government also introduced a policy which encourages mutual acknowledgment of test results across hospitals.

Prior to the HIE implementation, patient data was siloed within the hospital where the data was created. As hospitals adopted different information systems, patient data was scattered across hospitals, and it was difficult for hospitals to communicate with each other. The primary way to exchange health information was through a printed copy of medical records, handwritten paper medical records, or patient self-report.

The HIE implementation involved creating a centralized data repository which could provide authorized users (e.g., physicians) with secure and efficient access to data in it. The central data repository guaranteed a high level of interoperability as all the participating hospitals had to upload and retrieve health data in the same format and interpret the data in the same way. The HIE implementation also involved the integration between the central data repository and the existing systems in the hospital including hospital information systems (Agarwal et al.), electronic health record systems (EHR), laboratory information systems (LIS), picture archiving and communication systems (PACS), and radiology information systems (RIS). After the HIE system had been seamlessly integrated with the internal systems, these internal systems would upload patient data every day in an automatic manner. Data uploaded to the data repository included patients' demographic information, summaries of outpatient visits and inpatient admissions, medication histories, laboratory results, radiology images and reports, and clinical notes.

Physicians were authorized to search and view a patient's medical information via HIE at the point of care. From the physician's perspective, retrieving full patient data from HIE required little time and effort beyond a few clicks. A plug-in was installed in the physician workstation for accessing patient data via the HIE. Figure 1 shows the on-demand information retrieval process in the inpatient setting. Upon the physician's search request, the internal system would send the request to the central system which would in turn return the requested information from the central data repository.

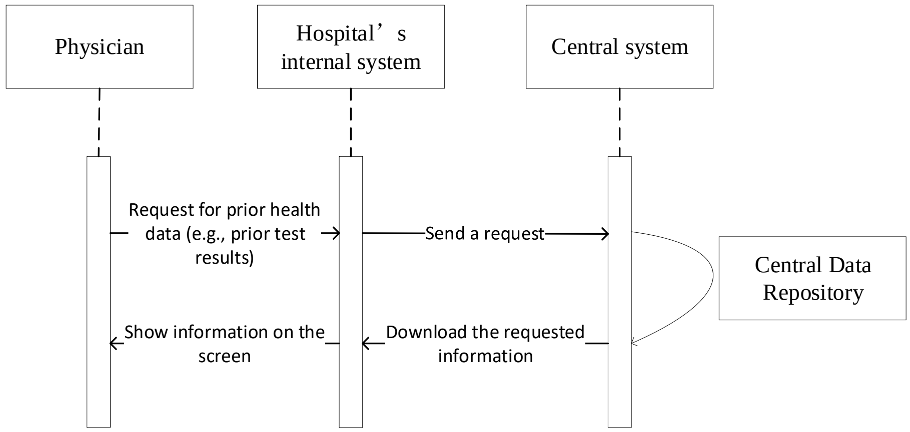

Figure 1 Information Retrieval Process

For the purpose of providing patients with access to HIE and creating patient files, the HIE project also involved assigning a unique identification number to each patient (hereinafter referred to as HIE ID number). The HIE ID number would be required for outpatient or inpatient admission registration in the 23 participating hospitals. The HIE ID number also allowed the patient to register and login to a portal to view their test results published by the hospital.

Importantly for our purposes, the HIE system was not accessible to patients all at once but instead rolled out over the course of one year. Beginning April 2008, the system was accessible to patients who subscribe to local public medical insurance plan (hereinafter referred to as subscribers) only. Subscribers were typically local residents or workers. The HIE ID number for the subscribers is the same as their insurance ID number. Whereas, there was no existing ID number that could be used as the HIE ID number for nonsubscribers. Nonsubscribers comprised mainly of patients from other cities and local residents who opted out of the local insurance plan. According to a report of local government, nonsubscribers had to obtain their HIE ID number by collecting physical ID card from one of the 23 participating hospitals. Because of technical constraints pertaining to preparing the physical ID cards, nonsubscribers did not have access to HIE until March 2009.

According to a public report by the HIE project, till the end of 2009, there had been around 11 million patient profiles, 30 million medical records, 150 million prescription records, 620,000 discharge summaries and 1.2 million test reports in the HIE data repository; 3000 test reports had been viewed by patients per month; the HIE had been used more than 90,000 times by all healthcare professionals per day, and the response time per search request was less than 5 seconds.

Data and Variables

We obtained a full dataset containing all discharge records generated by the hosipital hnformation system (HIS) in the focal hospital. The dataset provides data on medical expenditure of each hospitalization and patient data including gender, age, disease description, etc. Our data spans 13 months from September 2007 to September 2008. As HIE was implemented in March 2008, hospitalizations occurring in March 2008 or hospitalizations beginning before March 2008 but ending after March 2008 were not included for model estimation. The final dataset contains 59,129 hospitalizations in 39 departments over 52 weeks (26 weeks before and 26 weeks after the HIE implementation).

Medical costs. The total medical expenditure of a hospitalization episode could be disaggregated into six categories provided in the dataset. The six categories and examples of items in each category are reported in table 1. In our study, the test costs are measured as the aggregate costs of lab tests and radiology tests, and the medication costs include the costs of all kinds of medications prescribed during the hospital. Furthermore, we use a monthly CPI to adjust the medical costs for inflation. The log-transformed inflation-adjusted test costs, *Test Cost*, and medication costs, *MedCost* are the dependent variables of interest.

Table 1 Medical Cost Categories

Category	Examples of item

1. Lab Test	Blood test, urinalysis
2. Radiology Test	Ultrasonography, X-ray, electrocorticography, Intraocular pressure examination, CT scan, Magnetic Resonance Imaging (MRI), Digital subtraction angiography (DSA), medical examination
3. Medication	Western drug, Chinese patent medicine, Chinese herbal drug
4. Surgery & Material	Surgery, anesthesia, surgical materials & instruments, other medical materials
5. Specialty Treatment	Consultation, infrared therapy, dressing change, traction
6. Miscellaneous	Bed, meal, nursing care

Access to HIE. Our dataset provides information regarding whether the patient is a subscriber of the local public insurance plan. Our assignment of observations to treatment and control groups creates the binary variable, *Group*, which takes on a value of 1 if the inpatient is a subscriber of the local public insurance plan, otherwise 0. A econd binary variable, *Post*, takes on a value of 1 if the hospitalization took place after the HIE implementation, otherwise 0. Our central independent variable of interest is the treatment variable *HIE*, which is the interaction term between *Group* and *Post*. *HIE* measures whether the patient had access to HIE when he/she was admitted.

Hospitalization-level control variables. To obtain robust estimates of the effect of access to HIE, we control for potentially confounding factors at the hospitalization level. First, we control for patient gender, age, the severity of illness, comorbidity, admission type. Comorbidity was assessed based on whether a second condition was indicated in the dataset. The admission types included admissions from outpatient, emergency admissions and hospital transfers. We also control for the accumulated number of times that the patient had been admitted in the focal hospital since September 2006 (*N_hosp*). A binary variable indicating whether the patient had been discharged in the same department in the previous 30 days (*IfReadmission*) was also included. Furthermore, the ICD 10 diagnosis code in the dataset allows us to categorize observations into 189 disease types according to ICD 10 subchapters.

"Within-department" spillover. To measure the spillover effects, we consider the percentage of patients having access to HIE over the total number of admissions in the department in a week, *PercHIE*. We consider admissions rather than discharges because diagnostic tests usually take place at the initial stage of hospitalization, and thus the percentage of HIE admissions could represent how the department revenue could be affected. To examine the differences in the spillover effects across high-demand and low-demand departments, we measure the bed demand of departments (=number of patients admitted/number of available beds) in the pre-treatment period and then use the mean value as the cutoff value to indicate if a department is low-demand or high-demand. Using bed information of 31 departments, we categorize 19 departments as low-demand departments and 12 departments as high-demand departments.

Department-level control variables. To account for possible confounding occurring at the department level, we also control for department-weekly level variables including number of admissions and admission composition by treatment assignment, gender, age, the severity of illness. etc. Table 2 presents the summary statistics for the dependent variables, main independent variables, and control variables used in the analysis.

Table 2 Descriptive Statistics

Variable	Mean (%)	Standard Deviation	Min	Max
Dependent variables				
TestCost (log transformed test costs)	6.79	1.75	0	10.71
MedCost (log transformed medication costs)	6.88	2.09	0	12.37
Independent variables				
HIE	0.233	0.423	0	1
PercHIE	0.242	0.276	0	1
Hospitalization-level control variables				
Group (control/treatment group)	0.46	0.50	0	1
Post (Before/after HIE implementation)	0.52	0.50	0	1
Age	47.17	22.64	0	106
N_Hosp (accumulated number of hospitalizations)	1.76	2.22	1	40
Comorbid (0=no comorbid disease; 1= comorbid	0.39	0.49	0	1
IfReadmission (discharged in previous 30 days or not)	0.09	0.28	0	1

Gender				
female	44.78%			
male	50.73%			
newborn infants	4.49%			
Severity (severity of illness)				
Not severe	96.77%			
Severe	2.22%			
Unknown	1.01%			
Admission (admission mode)				
1:from outpatient	77.06%			
2:Emergency admission	22.93%			
3:from another hospital	0.01%			
Department-weekly level control variables				
Num_adm (log transformed number of admissions)	4.104	1.086	0.69	5.78
Perc_treatgroup (percentage of patients in the treatment group)	0.487	0.198	0	1
Perc_male	0.528	0.207	0	1
Perc_severity	0.023	0.060	0	0.77
Perc_comorbid	0.399	0.243	0	1
Perc_admission1	0.770	0.157	0	1
Perc_admission2	0.230	0.157	0	1
Perc_readmission	0.091	0.127	0	1
Perc_age1 (age 0-1)	0.017	0.071	0	0.5
Perc_age2 (age 2-17)	0.065	0.137	0	1
Perc_age3 (age 18-34)	0.247	0.245	0	1
Perc_age4 (age 35-64)	0.412	0.197	0	1
Perc_age5 (age>65)	0.260	0.226	0	1
Perc_hosp1 (N_Hosp=1)	0.758	0.209	0	1
Perc_hosp2 (N_Hosp=2)	0.111	0.079	0	1
Perc_hosp3 (N_Hosp>2)	0.131	0.177	0	1

Notes. Observations=59,129

Identification Strategies

We use the phased roll-out of the HIE as a natural experiment in order to understand the effect of access to HIE on the medical costs of a hospitalization episode. Our identification strategy for the impacts of access to HIE is based on the propensity score matching (PSM) and difference-in-difference (DID) methods. PSM is a method wherein treated observations and untreated observations are matched on the estimated probability of receiving treatment based on their observable characteristics, thereby creating a comparable counterfactual. DID is an analytical approach where variation across patients having access to HIE at difference times is exploited. The combination of PSM and DID, the MDID estimator, is also becoming increasingly popular as their combined strengths offset their individual weaknesses. The main appeal of this combined approach is that it mitigates both selection on observables (PSM) (e.g., in our context, if there are compositional changes across groups and across time) and selection on unobservables (DID) (e.g., in our context, if patients in the treatment group and the control group have different propensities to be admitted in the focal hospital). Our MDID approach would be valid if (1) conditional on the observables, the treatment group would have had the same trend in the dependent variable as the control group in the absence of intervention (common trend assumption); (2) and all treated individuals have a counterpart in each of the three control groups (common support assumption) (Blundell and Costa Dias 2009).

Propensity score is computed using a probit model with hospitalization characteristics as explanatory variables, i.e., (1) patient gender (Gender), (2) patient age (Age), (3) severity of illness (Severity), (4) Whether the hospitalization is a readmission (IfReadmission), (5) accumulated number of hospitalizations (N_hosp), (6) disease group based on ICD 10 chapters, and (7) department. We further included some quadratic and interaction terms to improve the quality of matching. These set of consumer covariates are comprehensive and informative, such that they influence the propensity of the patient being admitted and yet are not affected by the HIE implementation, thus satisfying the unconfoundedness identification assumption of PSM. We use kernel matching to match each of the control groups (control group before and after the HIE implementation and treatment group before the HIE implementation) to the treatment group after the HIE implementation. Epanechnikov kernel with a bandwidth equal to 0.05 is used to match treated observations with a weighted average of all controls with weights that are inversely proportional to the distance between propensity scores of treated and controls (i.e., exact matches are given a large weight, and poor matches a small weight). After matching, the standardized differences between the treated group and each of the control groups in terms of the above characteristics are below 0.1, indicating a satisfying covariate balance (Austin 2009). The sample restricted to the common support contains 54,574 observations, and it will be used for the main analysis.

Empirical Model

We estimate the following fixed-effect model for our main analysis:

$$\mathrm{Y_{ijt}} = \beta_1 \mathrm{HIE_{ijt}} + \beta_2 \mathrm{PercHIE_{i,t-1}} + \mathrm{X_{ijt}} + \mathrm{M_{i,t-1}} + \omega_t + u_i + \epsilon_{ijt} \qquad (1)$$

where $\mathrm{Y_{ijt}}$ is the log-transformed test cost or medication costs of a hospitalization episode j in the department i in time period t. β_1 is the DID estimate which captures the changes in $\mathrm{Y_{ijt}}$ for the treatment group relative to that of the control group. We consider department-level patient access to HIE in the previous period ($\mathrm{PercHIE_{i,t-1}}$) to avoid simultaneity issues and to allow for lagged spillover effects denoted by β_2. We include hospitalization-level controls ($\mathrm{X_{ijt}}$) such as gender, age, and severity in the regression model. We also control for department-level controls in the previous period ($\mathrm{M_{i,t-1}}$) such as the number of admissions and composition of admissions by gender, age and severity. ω_t denotes time period fixed effects; u_i represents department fixed effects; and ϵ_{ijt} is the error term.

To obtain the MDID estimate, we estimate the above regression model by specifying *pweight* option in Stata so that Stata uses the sampling weight produced by the kernel matching when computing estimates of the regression parameters.

Model Estimation and Results

Table 3 presents the results for Equation (1) where we estimate the direct and spillover effects of access to HIE on test costs and medication costs.

Effects on test costs. First, we find that some control variables explain the test costs (Table 3, column 1). For example, age, severity, and comorbidity have a positive effect on test costs while readmissions, the accumulated number of hospitalization and emergency admissions (compared to admission from outpatient) have a negative effect on test costs. In addition, as shown in table 3, column 2, the DID parameter estimate is -0.106, which is significantly negative. This implies a significant negative impact of 10.6% in test costs after having access to HIE. Patient access to HIE has a significant negative impact on test costs, which gives credence to further explore the spillover effects caused by income loss.

To the extent that differences in unobservables may result in pre-treatment heterogeneity in test costs across treatment and control group, these two groups would be incomparable in terms of test costs. To address this concern, we explicitly test parallel pretreatment trend in the regression where we include the interaction terms between a series of time dummies and the variable *Group*. We therefore model test costs using the following specification:

$$\mathrm{TestCost_{ijt}} = \sum_{s=1}^{S} \gamma_{0s} \mathrm{Pre_s} * \mathrm{Group_{ij}} + \sum_{s=1}^{S} \gamma_{1s} \mathrm{Post_s} * \mathrm{Group_{ij}} + \mathrm{X_{ijt}} + \eta_t + u_i + \epsilon_{ijt} \qquad (2)$$

where $\mathrm{Pre_s}$ is the indicator for the time period that is s periods before the HIE implementation. Thus, γ_{0s} measures the treatment group's differential change in $\mathrm{TestCost_{ijt}}$, where change is measured with respect to the baseline period (i.e., $\mathrm{Pre_1}$). We specify one month as a time period and there are 6 pre-treatment time periods (i.e., S=6). In addition, we include the interaction terms between indicators for each of the post-treatment time period and the variable Group to investigate the dynamics of the effect. As equation (1), hospitalization-level controls, department and disease type fixed effects are included. Month fixed effects are also included. Table 4 presents the results for equation (2). We see no significant differential effect between the two groups in each of the pre-treatment periods, with only one exception. We conclude that the common trend assumption of MDID model is not being violated. Furthermore, we see that the effect of access to HIE is insignificant initially, but become significant one month after the HIE implementation.

Effects on medication costs. As shown in Table 3, column 3 and column 4, some controls have a significant impact on medication costs, but the DID parameter estimate is not significant. We therefore focus on the spillover effects on medication costs. We find that *PercHIE* has no significant effect on medicine cost overall (Table 3, column 5), but the subsample analysis where we test the spillover effects in low-demand and high-demand departments (Table 3, column 6 and column 7) shows that *PercHIE* has a significant positive impact on medication costs for low-demand departments only. The estimates indicate that for low-demand departments, one more percentage of patients with access to HIE in the department increases the medication costs of all patients in the department by 0.479% (Table 3, column 6).

Table 3 Model Estimation Results

	(1) PSM, Control	(2) MDID	(3) PSM, Control	(4) MDID	(5) MDID, spillover	(6) MDID, spillover Low-demand	(7) MDID, spillover High-demand
VARIABLES	TestCost	TestCost	MedCost	MedCost	MedCost	MedCost	MedCost
HIE		-0.106*** (0.027)		-0.003 (0.030)	-0.005 (0.031)	0.004 (0.048)	-0.073** (0.037)
PercHIE					0.129 (0.090)	0.479*** (0.184)	-0.127 (0.106)
Group	0.016 (0.014)	0.071*** (0.019)	0.110*** (0.016)	0.112*** (0.022)	0.108*** (0.022)	0.164*** (0.035)	0.042 (0.026)
Post	-0.047 (0.034)	0.064* (0.038)	0.081** (0.038)	0.156*** (0.044)	-0.135 (0.127)	0.149 (0.148)	0.046 (0.123)
Gender	0.064*** (0.015)	0.064*** (0.015)	0.075*** (0.017)	0.075*** (0.017)	0.079*** (0.017)	0.089*** (0.025)	0.043** (0.022)
Age	0.006*** (0.001)	0.006*** (0.001)	0.013*** (0.001)	0.013*** (0.001)	0.013*** (0.001)	0.013*** (0.001)	0.009*** (0.001)
Severity	0.390*** (0.046)	0.390*** (0.046)	0.800*** (0.051)	0.800*** (0.051)	0.797*** (0.051)	0.588*** (0.060)	0.979*** (0.089)
Comorbidity	0.449*** (0.017)	0.449*** (0.017)	0.534*** (0.019)	0.534*** (0.019)	0.536*** (0.019)	0.637*** (0.030)	0.389*** (0.023)
Ifreadmission	-0.687*** (0.035)	-0.688*** (0.035)	0.374*** (0.032)	0.374*** (0.032)	0.376*** (0.032)	0.419*** (0.045)	0.126*** (0.045)
N_Hosp	-0.032*** (0.005)	-0.032*** (0.005)	0.024*** (0.006)	0.024*** (0.006)	0.024*** (0.006)	0.008 (0.008)	0.059*** (0.007)
Admission2	-0.214*** (0.020)	-0.214*** (0.020)	0.080*** (0.023)	0.080*** (0.023)	0.078*** (0.023)	0.217*** (0.032)	-0.092*** (0.032)
Admission3	-0.111 (0.339)	-0.140 (0.340)	0.028 (0.494)	0.027 (0.494)	-0.010 (0.499)	-1.188*** (0.101)	1.114** (0.519)
Num_Adm					-0.066 (0.045)	-0.016 (0.061)	-0.221*** (0.071)
Perc_treatgroup					0.071 (0.096)	0.164 (0.149)	-0.042 (0.113)
Perc_male					-0.281*** (0.103)	-0.321** (0.135)	-0.338* (0.175)
Perc_severity					-0.125 (0.297)	-0.432 (0.324)	0.105 (0.827)
Perc_comorbid					-0.030 (0.093)	0.159 (0.132)	-0.340** (0.139)
Perc_admission1					-1.269 (2.468)	-0.494 (3.032)	-6.391 (5.519)
Perc_admission2					-1.276 (2.465)	-0.615 (3.026)	-6.102 (5.523)
					-0.286*	-0.234	-0.346

Perc_readmission					(0.168)	(0.218)	(0.234)
Perc_age1					0.801 (1.258)	2.651 (2.799)	-1.195 (1.190)
Perc_age2					-0.199 (0.218)	-0.349 (0.290)	0.118 (0.353)
Perc_age3					0.171 (0.156)	0.140 (0.225)	-0.0454 (0.215)
Perc_age4					0.089 (0.107)	0.106 (0.150)	-0.120 (0.170)
Perc_hosp1					-0.024 (0.137)	0.132 (0.177)	-0.477** (0.234)
Perc_hosp2					-0.116 (0.155)	-0.392* (0.205)	0.0222 (0.259)
Department, week, disease category[a] fixed effects	Included	Included	Included	Included	Included	Included	Included
Number of departments	39	39	39	39	39	19	12
Observations	53,574	53,574	53,574	53,574	52,313	21,754	29,783
R-squared	0.443	0.443	0.518	0.518	0.519	0.375	0.617

Notes. *<0.1 **<0.05 ***0.01 robust standard error in parentheses.
a. A large number of disease categories were absorbed by the REGHDFE command in Stata and not reported.

Table 4 Pre-treatment Trend and Dynamics of the Effect

VARIABLES	TestCost
Group	0.129** (0.056)
pre6*group	0.003 (0.075)
pre5*group	-0.103 (0.069)
pre4*group	-0.048 (0.070)
pre3*group	-0.120* (0.071)
pre2*group	-0.063 (0.075)
pre1*group	(omitted)
post1*group	-0.0911 (0.074)
post2*group	-0.145** (0.069)
post3*group	-0.173** (0.071)
post4*group	-0.273*** (0.070)
post5*group	-0.139* (0.075)

post6*group	-0.162** (0.073)
Hospitalization-level controls	Included
Department, month, disease category fixed effects	Included
Number of departments	39
Observations	53,574
R-squared	0.444

Notes. *<0.1 **<0.05 ***0.01 robust standard error in parentheses.

The Mechanisms of the Spillover Effects

Income Loss. The primary mechanism for the spillover effects to occur is loss of department revenue which would in turn lead to loss of physician income. When more patients have access to HIE, the department is more likely to have lower revenues associated with testing. If this argument holds, we should observe a negative relationship between the percentage of discharged patients with access to HIE and the average test costs. We therefore average the test costs at the department-week level and estimate the effect of percentage of HIE patients in the discharges in a week on their average test costs. Five departments with too few observations (i.e, number of observations<12) are excluded. Table 5 presents the estimation results. We see that percentage of HIE patients in the discharges has a significant negative effect on the average test costs after controlling for the number of discharges, percentage of patients in the treatment group, and composition of discharges by other hospitalization characteristics. The estimates in Table 5 suggest that one more percentage of patients with access to HIE decreases the average test costs by 0.174%. This evidence indicates that patient access to HIE would be a revenue threat to the departments, which supports the income-loss mechanism.

Efficiency improvement. Our efficiency-improvement mechanism suggests that if departments could improve their efficiency and admit more patients, the spillover effects caused by income loss would be mitigated. We have shown that the spillover effects are not significant for high-demand departments. To test whether the insignificance is due to efficiency-improvement mechanism, we test whether high-demand departments (1) improve their efficiency, (2) and admitted more patients after the HIE implementation.

First, if high-demand departments improve their efficiency, we should observe a decrease in the inpatient length of stay. Table 6 shows the result where we test the effect of patient access to HIE on length of a hospital stay. We find that length of stay for patients who have access to HIE is shorter for high-demand departments only (Table 6, column 3). The hospital stays of patients who have access to HIE in high-demand departments are shortened by around 0.9 days. This evidence indicates that high-departments free up beds more quickly and enhance more in the capacity to accommodate more inpatient demand.

Table 5 Income Loss (Department-Week Analysis)

VARIABLES	(1) TestCost_Ave
PercHIE (in discharges)	-0.174* (0.102)
perc_treatgroup (in discharges)	0.278** (0.116)
Post	0.049 (0.128)
Num_Discharge	0.135** (0.053)
Composition of discharges by gender, age, severity, comorbidity, readmission, admission type, and N_hosp	Included
Department, week fixed effects	Included
Number of departments	34
Observations	1,736
R-squared	0.832

Notes. *<0.1 **<0.05 ***0.01 robust standard error in parentheses.

Table 6 Efficiency Improvement by Demand of Department

	(1)	(2)	(3)
	FULL	Low-demand departments	High-demand departments
VARIABLES	lengthofstay	lengthofstay	lengthofstay
HIE	-0.478	-0.380	-0.904**
	(0.337)	(0.525)	(0.457)
Group	-0.546*** (0.166)	-0.598** (0.278)	-0.161 (0.178)
Post	3.231 (2.049)	5.191 (3.688)	1.346 (1.463)
PercHIE	-0.961 (0.985)	2.706 (2.462)	-0.647 (0.900)
Hospitalization- and department- level controls	Included	Included	Included
Department, disease category, week fixed effects	Included	Included	Included
Number of departments	39	19	12
Observations	55,051	22,106	30,330
R-squared	0.132	0.167	0.069

Notes. *<0.1 **<0.05 ***0.01 robust standard error in parentheses.

Second, we attempt to assess whether the high-demand departments indeed meet more demand after the HIE implementation. As the number of available beds largely constrain the demand that could be met, we control for it by measuring the met demand as bed demand (i.e., the number of admissions divided by the number of available beds). We conduct a department-weekly level analysis to test the effect of the percentage of patients with access to HIE (*PercHIE)* in the previous period on the met bed demand. We expect that *PercHIE* in previous period would have a positive effect on the met bed demand. The results in Table 7 show that the effect of *PercHIE* on the met bed demand is not significant for both low-demand and high-demand departments. However, we see that the effect is positive and larger in magnitude for high-demand departments. One possibility is that the high-demand departments did not respond quickly to the increased capacity immediately after the HIE implementation. To explore this possibility, we dropped the four weeks immediately after the HIE implementation and re-estimate the model. The results show that percentage of patients having access to HIE admitted in the previous period has a positive effect on the met bed demand after dropping the weeks immediately after the HIE implementation.

Table 7 Changes in Bed Demand by Demand of Department (Department-Week Analysis)

	(1) FULL	(2) Low-demand departments	(3) High-demand departments
VARIABLES	BedDemand	BedDemand	BedDemand
PercHIE	0.057 (0.042)	0.023 (0.026)	0.113 (0.080)
Post	0.084* (0.048)	0.068*** (0.026)	0.028 (0.088)
Perc_treatgroup	-0.147*** (0.048)	-0.056** (0.023)	-0.326** (0.165)
Department-weekly level controls	Included	Included	Included
Department, week fixed effects	Included	Included	Included
Number of departments	31	19	12
Observations	1,571	947	624
R-squared	0.863	0.790	0.830

Notes. *<0.1 **<0.05 ***0.01 robust standard error in parentheses.

Table 8 Changes in Bed Demand by Demand of Department (Department-Week Analysis)

	three weeks immediately after HIE implementation are dropped	four weeks immediately after HIE implementation are dropped

	(1) FULL	(2) Low-demand departments	(3) High-demand departments	(4) FULL	(5) Low-demand departments	(6) High-demand departments
VARIABLES	BedDemand	BedDemand	BedDemand	BedDemand	BedDemand	BedDemand
PercHIE	0.0663 (0.0427)	0.0192 (0.0265)	0.147* (0.0812)	0.0729* (0.0426)	0.0158 (0.0269)	0.168** (0.0802)
Post	0.0782* (0.0424)	0.0674** (0.0300)	0.0564 (0.0908)	0.0938** (0.0412)	0.0690** (0.0302)	0.183 (0.128)
Perc_treatgroup	-0.150*** (0.0487)	-0.0547** (0.0228)	-0.327* (0.170)	-0.147*** (0.0490)	-0.0569** (0.0230)	-0.303* (0.174)
Department-weekly level controls	Included	Included	Included	Included	Included	Included
Department, week fixed effects	Included	Included	Included	Included	Included	Included
Number of departments	31	19	12	31	19	12
Observations	1,480	892	588	1,450	874	576
R-squared	0.867	0.785	0.838	0.867	0.785	0.840

Discussion and Contribution

Our study investigates the direct and spillover effects of patient access to HIE on medical costs and it has several notable findings. First, we empirically show that patient access to HIE leads to a significant decrease in the test costs of a hospitalization episode. Thus, H1 is supported. Second, our study shows that patient access to HIE has spillover effects on medication costs of patients in the same department for low-demand departments only. Hence, H2a is not supported, and H2b is supported. Our in-depth examination of spillover effects of HIE access shows that income loss and efficiency improvement provide mechanisms that could drive or mitigate spillover effects. Understanding these spillover effects helps shed light on whether patient access to HIE leads to a reduction in medical costs at the macro level.

Theoretical Contributions and Practical Implications

This study makes contributions to the literature in several ways. First, this study provides an in-depth examination of the impact of access to HIE on both test costs and medication costs. While prior studies have explicitly or implicitly presumed that HIE could reduce both test costs and other medical costs, our findings suggest differential and even contrasting effects of HIEs on test costs and medication costs. The medical cost savings resulting from a reduction in test costs would be compromised by an increase in medication costs.

In contrast to prior research evaluating HIT investment payoff, our research is among the first to incorporate the consequence of divide in access to HIT when investigating the impact of patient access to HIT on medical costs. To this end, we consider both department- and hospitalization-level mechanisms. We find that at the hospitalization level, HIEs could lower test costs through reduction in redundancy of diagnostic testing. Moreover, we look beyond the hospitalization level and consider the financial impacts of HIE at the department level. At the department level, access to HIE creates spillover effects on medication costs so that divide in access does not lead to a difference in medication costs but both groups experience an increase in medication costs. Our in-depth examination of spillover effects attests to the fact that income-loss and efficiency-improvement mechanisms could influence the occurance of the spillover effects of patient access to HIE. Our findings underscore that addressing the physician's concerns about income loss is important to attenuate the spillover effects.

Lastly, this study extends to the literature on physician agency. Prior studies have investigated the response of physicians to the income shock due to change in service fee or physician-population ratio. Our findings indicate that patient access to HIE would lead to a negative income shock and it would also motivate the physicians to compensate for the income loss. We accentuate the role of physicians in achieving effective cost control such that use of HIE may ironically increase medical costs due to physicians' financial concerns and exploitation of the inherent information asymmetry between patient and physician.

Our study quantifies the benefits of access to HIE as a mean to reduce test costs. Consistent with the intent of HIE implementation, our results show that patient access to HIE can significantly reduce the inpatient test costs. Our result implies a significant negative impact of 10.6% in test costs after having access to HIE. There is a need to promote regional HIEs and encourage patient as well as healthcare providers to adopt HIEs for obviating redundant tests. We also find that use of HIE may unexpectedly cause an increase in medication costs in a traditional fee-for-service setting. In the fee-for-service setting, physicians' incomes are dependent on the quantities of services. The benefits of access to HIE in reducing test costs could become a financial concern to healthcare providers. The government should watch out for demand inducement which could be intensified by the physician use of HIE. The government needs to align the incentives for healthcare providers to discourage profit-making activities that drive medical costs. Without financing reforms that detach the physician's incentives from health services charges, investments in HIEs might actually aggravate the inefficiency problem. Indeed, the transformation from the traditional fee-for-service payment model to outcome-based payment model has shown some promising results in medical cost containment. The government might also need to help the hospital to address financial challenges by increasing subsidy for the hospital. Shortage of public funds has certainly been the main motivation for public hospitals to seek private payments.

Reference

Agarwal, R., Gao, G., DesRoches, C., and Jha, A. K. 2010. "The Digital Transformation of Healthcare: Current Status and the Road Ahead," *Information Systems Research* (21:4), pp. 796-809.

Ambra Health. 2017. "Era of Change: Today's Healthcare Consumer." from https://ambrahealth.com/ebook/era-change-todays-healthcare-consumer/

Austin, P. C. 2009. "Using the Standardized Difference to Compare the Prevalence of a Binary Variable between Two Groups in Observational Research," *Communications in Statistics - Simulation and Computation* (38:6), pp. 1228-1234.

Ayabakan, S., Bardhan, I., Zheng, Z. E., and Kirksey, K. 2017. "The Impact of Health Information Sharing on Duplicate Testing," *MIS Quarterly* (41:4), pp. 1083-1103.

Bailey, J. E., Pope, R. A., Elliott, E. C., Wan, J. Y., Waters, T. M., and Frisse, M. E. 2013. "Health Information Exchange Reduces Repeated Diagnostic Imaging for Back Pain," *Annals of Emergency Medicine* (62:1), pp. 16-24.

Bates, D. W., Boyle, D. L., Rittenberg, E., and Kuperman, G. J. 1998. "What Proportion of Common Diagnostic Tests Appear Redundant?," *The American Journal of Medicine* (104:4), pp. 361-368.

Bates, D. W., Kuperman, G. J., Jha, A., Teich, J. M., Orav, J., Ma'luf, N., Onderdonk, A., Pugatch, R., Wybenga, D., Winkelman, J., Brennan, T. A., Komaroff, A. L., and Tanasijevic, M. J. 1997. "Does the Computerized Display of Charges Affect Inpatient Ancillary Test Utilization?," *Archives of Internal Medicine* (157:21).

Becher, E. C., and Chassin, M. R. 2001. "Improving the Quality of Health Care: Who Will Lead?," *Health Affairs* (20:5), pp. 164-179.

Blaya, J. A., Fraser, H. S. F., and Holt, B. 2010. "E-Health Technologies Show Promise in Developing Countries," *Health Affairs* (29:2), pp. 244-251.

Blundell, R., and Costa Dias, M. 2009. "Alternative Approaches to Evaluation in Empirical Microeconomics," *Journal of Human Resources* (44:3), pp. 565-640.

Earle, M. J. T. Y. C. J. P. N. C. C. 2013. "Physician Agency and Competition: Evidence from a Change to Medicare Chemotherapy Reimbursement Policy," in: *National Bureau of Economic Research*.

Evans, R. G. 1974. "Supplier-Induced Demand: Some Empirical Evidence and Implications," in *The Economics of Health and Medical Care*. Springer, pp. 162-173.

Fan, R. 2007. "Corrupt Practices in Chinese Medical Care: The Root in Public Policies and a Call for Confucian-Market Approach," *Kennedy Institute of Ethics Journal* (17:2), pp. 111-131.

Frisse, M. E. 2010. "Health Information Exchange in Memphis: Impact on the Physician-Patient Relationship," *Journal of Law, Medicine & Ethics* (38:1), pp. 50-57.

Frisse, M. E., and Holmes, R. L. 2007. "Estimated Financial Savings Associated with Health Information Exchange and Ambulatory Care Referral," *Journal of Biomedical Informatics* (40:6), pp. S27-S32.

Frisse, M. E., Johnson, K. B., Nian, H., Davison, C. L., Gadd, C. S., Unertl, K. M., Turri, P. A., and Chen, Q. 2012. "The Financial Impact of Health Information Exchange on Emergency Department Care," *Journal of the American Medical Informatics Association* (19:3), pp. 328-333.

Gruber, J., Kim, J., and Mayzlin, D. 1999. "Physician Fees and Procedure Intensitya: The Case of Cesarean Delivery," *Journal of Health Economics* (18:4).

Gruber, J., and Owings, M. 1996. "Physician Financial Incentives and Cesarean Section Delivery," *The RAND Journal of Economics* (27:1), pp. 99-123.

Handel, D. A., Hilton, J. A., Ward, M. J., Rabin, E., Zwemer, F. L., Jr., and Pines, J. M. 2010. "Emergency Department Throughput, Crowding, and Financial Outcomes for Hospitals," *Academic Emergency Medicine* (17:8), pp. 840-847.

Kaelber, D. C., and Bates, D. W. 2007. "Health Information Exchange and Patient Safety," *Journal of Biomedical Informatics* (40:6), pp. 40-45.

Lang, E., Afilalo, M., Vandal, A. C., Boivin, J. F., Xue, X., Colacone, A., Leger, R., Shrier, I., and Rosenthal, S. 2006. "Impact of an Electronic Link between the Emergency Department and Family Physicians: A Randomized Controlled Trial," *Canadian Medical Association Journal* (174:3), pp. 313-318.

Liu, X., Liu, Y., and Chen, N. 2000. "The Chinese Experience of Hospital Price Regulation," *Health Policy and Planning* (15:2), pp. 157-163.

Lundin, D. 2000. "Moral Hazard in Physician Prescription Behavior," *Journal of Health Economics* (19:5), pp. 639-662.

McGuire, T. G. 2000. "Physician Agency," in *Handbook of Health Economics,* A.J. Culyer and J.P. Newhouse (eds.). Elsevier, pp. 461-536.

McGuire, T. G., and Pauly, M. V. 1991. "Physician Response to Fee Changes with Multiple Payers," *Journal of Health Economics* (10:4), pp. 385-410.

Menon, N. M., Lee, B., and Eldenburg, L. 2000. "Productivity of Information Systems in the Healthcare Industry," *Information Systems Research* (11:1), pp. 83-92.

Menon, N. M., Yaylacicegi, U., and Cezar, A. 2009. "Differential Effects of the Two Types of Information Systems: A Hospital-Based Study," *Journal of Management Information Systems* (26:1), pp. 297-316.

Miller, A. R., and Tucker, C. 2014. "Health Information Exchange, System Size and Information Silos," *Journal of Health Economics* (33), pp. 28-42.

Ministry of Health of China. 2018. " Chinese Health Statistics Yearbook." Beijing: People's Health Press.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., and Podsakoff, N. P. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies.," *Journal of Applied Psychology* (88:5), pp. 879-903.

Teich, J. M., Merchia, P. R., Schmiz, J. L., Kuperman, G. J., Spurr, C. D., and Bates, D. W. 2000. "Effects of Computerized Physician Order Entry on Prescribing Practices," *Archives of Internal Medicine* (160:18), pp. 2741-2747.

Tzeel, A., Lawnicki, V., and Pemble, K. R. 2011. "The Business Case for Payer Support of Community-Based Health Information Exchange: A Humana Pilot Evaluating Its Effectiveness in Cost Control for Plan Members Seeking Emergency Department Care," *American Health & Drug Benefits* (4:4), pp. 207-215.

Walker, J., Pan, E., Johnston, D., Adler-Milstein, J., Bates, D. W., and Middleton, B. 2005. "The Value of Health Care Information Exchange and Interoperability," *Health Affairs* (24), pp. W5-10.

Watcharasriroj, B., and Tang, J. C. S. 2004. "The Effects of Size and Information Technology on Hospital Efficiency," *The Journal of High Technology Management Research* (15:1), pp. 1-16.

Wei, K.-K., Teo, H.-H., Chan, H. C., and Tan, B. C. Y. 2011. "Conceptualizing and Testing a Social Cognitive Model of the Digital Divide," *Information Systems Research* (22:1), pp. 170-187.

Yip, W., and Eggleston, K. 2004. "Addressing Government and Market Failures with Payment Incentives: Hospital Reimbursement Reform in Hainan, China," *Social Science & Medicine* (58:2), pp. 267-277.

Yip, W., and Hsiao, W. 2014. "Harnessing the Privatisation of China's Fragmented Health-Care Delivery," *The Lancet* (384:9945), pp. 805-818.

Yip, W. C. 1998. "Physician Response to Medicare Fee Reductions: Changes in the Volume of Coronary Artery Bypass Graft Cabg Surgeries in the Medicare and Private Sectors," *Journal of Health Economics* (17:6), pp. 675-699.