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The Spillover Effects of Health IT Investments on Regional Healthcare Costs

Hilal Atasoy,[a] **Pei-yu Chen,**[b] **Kartik Ganju**[c]

[a] Fox School of Business, Temple University, Philadelphia, Pennsylvania 19122; [b] W. P. Carey Information Systems, Arizona State University, Tempe, Arizona 85287; [c] Desautels Faculty of Management, McGill University, Montreal, Quebec H3A 1G5, Canada

Contact: hilal.atasoy@temple.edu (HA); peiyu.chen@asu.edu (PC); kartik.ganju@mcgill.ca (KG)

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Abstract. Electronic health records (EHR) are often presumed to reduce the significant and accelerating healthcare costs in the United States. However, evidence on the relationship between EHR adoption and costs is mixed, leading to skepticism about the effectiveness of EHR in decreasing costs. We argue that simply looking at the hospital-level effects can be misleading because the benefits of EHR can go beyond the adopting hospital by creating regional spillovers via information and patient sharing. When patients move between hospitals, timely and high-quality records received at one hospital can affect the costs of care at another hospital. We provide evidence that although EHR adoption increases the costs of the adopting hospital, it has significant spillover effects by reducing the costs of neighboring hospitals. We further show that these spillovers are linked to information and patient sharing. Specifically, the spillovers are stronger when more hospitals in the region are in health information exchange networks and in the same integrated delivery systems, which can share information more easily. Furthermore, utilizing regional characteristics that can affect the extent of patient sharing such as urban versus rural areas, population density, average distance between hospitals, and hospital density, we find that locations with higher patient and hospital concentration experience stronger regional spillovers. Additionally, spillovers are stronger after the HITECH (Health Information Technology for Economic and Clinical Health) Act that increased EHR adoption and use. Overall, our findings suggest that we need to take into account externalities to understand the benefits of health IT investments and form policy decisions.

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Keywords: network externality • IT spillovers • health IT • electronic health records • IT productivity

1. Introduction

The cost of healthcare continues to be the subject of several policy debates in the United States. In 2014, healthcare expenditure was $3.0 trillion (Centers for Disease Control and Prevention 2015), and this figure is estimated to grow to $5.1 trillion by 2023, outpacing the expected growth rate in GDP in the corresponding period (Congressional Budget Office 2008, U.S. Centers for Medicare and Medicaid Services 2010). The U.S. healthcare system is criticized as being uncoordinated and fragmented, leading to inefficient resource allocation that has an estimated operational waste between $126 billion and $315 billion (PricewaterhouseCoopers 2008). Considering the alarming level and growth of medical costs, it has been a primary interest of policy makers to find possible solutions to mitigate them. One example is the Health Information Technology for Economic and Clinical Health Act (HITECH Act), which allocates around $19 billion to increase EHR adoption by healthcare providers. The policy provides financial incentives for digitizing records, as well as imposing penalties on institutions that do not comply. The underlying belief for these public subsidies is that EHR adoption would lower the healthcare costs and improve the quality of care. EHR is expected to improve health record keeping and retrieval, and enhance care coordination and information exchange both within and across hospitals, which in turn can translate into lower costs with a reduction in preventable medical errors, unnecessary readmissions, over-testing, and emergency room (ER) visits.

While substantial evidence exists on the positive effect that EHR adoption can have on clinical *quality*, evidence regarding the effect of EHR on healthcare *costs* is more scarce and mixed (Jones et al. 2012). The conflicting findings question the role of EHR in healthcare providers' productivity and the effectiveness of EHR as a policy tool that facilitates cost reductions. However, this debate is not unique to EHR, as a similar paradox created a large body of research about the impact of general IT investments on productivity (e.g., Brynjolfsson and Hitt 1996, 2003; Dedrick et al. 2003; Lichtenberg 1995). The IT productivity literature shows that organizations achieve gains from IT investments as they make several complementary changes in their business processes (e.g., Bresnahan and Greenstein 1996, Brynjolfsson et al. 2002). Notably, some studies provide evidence that there are substantial IT productivity spillovers among interconnected firms of the same network, such as supply chains, industries, and regional clusters, via coordination and labor sharing (Bloom et al. 2013; Chang and Gurbaxani 2012; Cheng and Nault 2007, 2012; Han et al. 2011; Tambe and Hitt 2014). Similarly, hospitals in the same region are considered to be a network, affecting one another's outcomes through cross-hospital externalities arising from shared patients (Huang et al. 2010, Landon et al. 2012, Lee et al. 2011). A significant portion of patients in a hospital are drawn from the same pool of potential patients as the other hospitals located in the same area, and studies show that hospitals in a region often share patients (Lee et al. 2011). Other studies that focus on the physician networks define the ties between physicians as shared patients and document that physicians of different hospitals share patients (Barnett et al. 2011, 2012; Landon et al. 2012).

Combining the IT spillovers and hospital network literatures, we argue that interhospital information and patient sharing can create a link between the EHR adoption of one hospital and the costs of another hospital. When a patient transfers between two hospitals, *better records and timely information availability* about the patient in one hospital can facilitate coordination of care with better knowledge about diagnosis, complications, and procedures in another hospital. The improved knowledge and care coordination can increase care quality and prevent redundancy (Ayabakan et al. 2014, Lammers et al. 2014), and thus reduce costs for the second hospital. This mechanism suggests that there are potential spillover effects in a network of hospitals that are likely to share information and patients.

Our goal in this research is to quantify the spillover effects of EHR adoption by hospitals on the costs of neighboring hospitals in the same Hospital Service Area (HSA), and to analyze the mechanisms through which such EHR spillovers can occur. We use data from several sources to link EHR adoption to the costs and other characteristics of hospitals between 1998 and 2012. A hospital fixed-effects model is used for the main specifications, and we address the endogeneity issues with several tests. Our findings provide significant evidence for cross-hospital externalities and show that EHR adoption, while costly for the adopting hospitals as they incur high expenditures, can lead to reductions in cost for other hospitals in the area and in aggregate healthcare costs.

We further investigate how regional EHR spillovers are related to information- and patient-sharing mechanisms that provide the linkage among hospitals in a network. To test the information-sharing mechanism, we exploit variations in the number of hospitals in the region that are in a health information exchange (HIE) and integrated delivery systems (IDS), as hospitals in HIE networks and IDS franchises have a higher likelihood of information exchange due to higher data interoperability and lower barriers of information sharing. Our results show that the spillover effects are stronger if more hospitals in the region are in HIE and IDS networks, supporting the idea that information sharing among hospitals facilitates spillovers of EHR investments. Additionally, we examine how patient sharing affects regional EHR spillovers. The need for information sharing is triggered by patients moving across hospitals, and we expect the spillovers to be stronger when the number of shared patients increases. We use regional characteristics that can affect the likelihood and magnitude of patient sharing among hospitals. Specifically, we expect higher level of patient sharing as population and hospital concentration in the area increase. We utilize four measures: (1) urban versus rural areas, (2) population density (population per square mile), (3) average distance between hospitals in the area, and (4) hospital density (hospitals per square mile). We find stronger spillovers for urban locations, areas with higher population and hospital density, and areas where hospitals are more closely located, providing evidence that shared patients are related to regional EHR externalities. Overall, our results indicate that information and patient sharing play important roles in shaping up regional EHR externalities. Additionally, we analyze whether the spillover effects are different before and after the HITECH Act of 2009 that increased EHR adoption and use substantially, and we find that regional spillovers are stronger after the HITECH Act, providing evidence that externalities increase as neighboring hospitals increase their EHR levels.

We make several contributions to the literature on the relationship between EHR adoption and healthcare costs, and provide important public policy implications. We present a theoretical framework and empirical evidence on the regional spillover effects of EHR adoption and thus add to the literature that mainly focuses on hospital-level impacts. Our findings suggest that we need to look beyond the hospital level to examine EHR as a potential solution to reducing overall healthcare costs and understand its macroeconomic impact. Increased data interoperability and ease of information sharing among the hospitals can increase the positive externalities of EHR and therefore increase the value of EHR investments in reducing aggregate healthcare costs.

2. Literature Review and Theoretical Development

2.1. The Effects of EHR Adoption on Adopting Hospitals' Costs

There can be at least two forces through which EHR adoption impacts operational costs *for the adopting* *hospital.* First, EHR systems are expensive and therefore will directly increase the costs, especially during the initial implementation. EHR adoption can also increase the costs in the subsequent years, as these systems require significant maintenance and update costs. For example, typical installation costs range between $3 million for a 250-bed hospital and $7.9 million for a 500-bed hospital, along with corresponding yearly maintenance costs ranging between $700,000 and $1.35 million (Congressional Budget Office 2008).

On the other hand, these technologies can introduce several improvements that can in turn lead to cost reductions. EHR applications are usually found to affect patient outcomes and increase healthcare quality by enabling diagnostics and decision-making tools for physicians, better patient control and tracking, and improved patient safety, especially for more complex cases in which patients require the regular collaboration of different departments (Athey and Stern 2000, Buntin et al. 2011, Chaudhry et al. 2006, McCullough et al. 2016, Miller and Tucker 2011, Parente and McCullough 2009). These improvements in healthcare quality can decrease the waste that is prominent in the United States healthcare system. EHR can reduce costs by decreasing medical errors through better caregiver coordination and record keeping among the different departments in a given hospital. Improved care quality and coordination can further decrease the costs by preventing redundant tests, unnecessary readmissions, and ER visits.

Empirical evidence on the relationship between EHR adoption and healthcare costs is characterized by inconclusive and conflicting results. Hillestad et al. (2005) used results from previous studies and extrapolated the net potential cost savings of EHR adoption after the initial costs. They estimated that if 90% of U.S. hospitals adopted EHR, potential savings could add up to $80 billion over 15 years. These efficiency savings are estimated to arise from avoidance of adverse drug events, improvement in disease prevention, and management of chronic diseases. However, the assumptions of this study, for example that EHR completely replaces the need for a physician's clerical staff, are challenged and argued to be unrealistic (Sidorov 2006). Borzekowski (2009) analyzed whether the early versions of health IT applications changed hospital-level costs using panel data from 1987 to 1994. The study found that hospitals adopting the most automated systems had cost reductions within a five-year period. Additionally, hospitals that implemented less-automated EHR systems incurred an increase in cost levels. Recent studies that evaluate a more comprehensive set of EHR systems at the hospital level found that EHR adoption usually increases operational costs (Agha 2014). Dranove et al. (2014) found an increase in hospital costs with EHR adoption, on average. This study demonstrated the importance of complementary resources in achieving benefits from EHR, and found that only hospitals in IT-intensive locations experienced cost reductions. Overall, based on the evidence in the literature, it is unclear whether hospitals can absorb the hefty adoption costs of EHR systems.

2.2. The Spillover Effects of EHR Adoption on Regional Healthcare Costs

Previous studies have focused on the hospital-level effects of EHR adoption, which are certainly important. However, the impacts of EHR adoption can surpass the adopting hospital, as there can be regional externalities. Our theoretical foundation for the spillover effects of EHR adoption is drawn on two literature streams: IT spillovers and hospital networks.

There is a vast literature on network externalities starting with Katz and Shapiro (1985). Several technologies such as electronic data interchange are subject to such externalities (e.g., Markus et al. 2006, Zhu et al. 2006). Information systems (IS) research documents that firms can benefit from IT investments of other firms through mechanisms such as interindustry transactions, trading, and labor mobility (Bloom et al. 2013; Chang and Gurbaxani 2012; Cheng and Nault 2007, 2012; Han et al. 2011; Tambe and Hitt 2014). Cheng and Nault (2007) found that gains from IT investments in upstream industries pass down to downstream industries, as suppliers' improved products and demand forecasts due to IT benefit the customer firms. Similarly, customer firms' IT investments can spill over to suppliers with enhanced exchange of more accurate information (Cheng and Nault 2012). Thus, the benefits of IT can spill over across the supply chain via better coordination and efficiency. There can also be IT productivity spillovers among the firms that do not engage in transactions—for example, via labor mobility. Firms realize knowledge spillovers related to IT investments of other firms from which they hire labor (Tambe and Hitt 2014). Studies also show that the IT contributions to output exceed private IT returns, which implies that IT investments have externalities that are economically significant and contribute to long-term productivity (Brynjolfsson and Hitt 1995).

In the context of healthcare, we expect network externalities to arise from information and patient sharing among hospitals, which are consistent with both *coordination and efficiency-spillover* arguments in the IT productivity literature. Hospitals that are geographically colocated are considered to be a network. They are often connected through shared patients, because patients are treated at or admitted to different hospitals in the same region (Huang et al. 2010, Lee et al. 2011). Lee et al. (2011) conducted a detailed social-network analysis of hospitals in Orange County, California, and found that 87% of hospitals shared patients. Studies that focus on physician networks measured the links between physicians by the number of shared patients and documented that physicians at different hospitals share patients and information about the patients (Barnett et al. 2011, 2012; Landon et al. 2012). Huang et al. (2010) found significant effects of patient sharing on hospital outcomes related to the spread and control of infectious diseases, patient education, and prevention programs.

Patient mobility can create EHR spillover effects. As an example, consider a cancer patient who is diagnosed and treated at hospital A for a certain time, and this hospital is equipped with advanced EHR systems that enabled an accurate diagnosis and high-quality care for the patient, as well as good electronic records for her history. When this patient transfers to hospital B, this transfer might reflect in the costs of hospital B. *Availability of timely information and high-quality records* about the patient's history, diagnosis, procedures, and complications facilitated by EHRs of hospital A can improve *patient care coordination* at hospital B. Patient care coordination refers to the integration of care in consultation with patients and their caregivers across all patient conditions, needs, clinicians, and settings (O'Malley et al. 2009). Poor documentation and communication failure are two main reasons for fragmentation of care coordination. Better patient records can lead to higher quality of care and lower costs via lower medical errors, lower readmissions, and reductions in duplicate testing within and across settings. For example, Lammers et al. (2014) found that patient information sharing across hospitals leads to lower repeated imaging. Patients were 59% less likely to have a redundant CT scan, 44% less likely to get a duplicate ultrasound, and 67% less likely to have a repeated chest x-ray when both their emergency visits were at hospitals that shared information across an HIE. Similarly, Ayabakan et al. (2014) find that interhospital information sharing is associated with lower levels of duplicate radiology imaging when patients switch between hospitals.

Information sharing can also impact physician productivity. Bhargava and Mishra (2014) categorize the interactions of physicians with EHR as *information review* and *information entry*. Physicians can retrieve, review, and analyze existing information in the EHR systems to learn about a patient's current and past conditions, and to achieve improved diagnosis and decision making. Physicians also enter and document patient conditions, diagnoses, treatments, and test results in EHR systems. The authors find that while the productivity of physicians who bear a data entry burden (such as family physicians and pediatricians) decreases, the productivity of other physicians who use and review these data increases. This provides evidence for externalities from information sharing at the physician level, which may or may not turn into reduced costs for the hospital.

EHR systems improve health record keeping and retrieval; however, EHR systems by themselves do not necessarily guarantee a timely and seamless electronic exchange of information between hospitals due to incompatible systems or other barriers such as competition among hospitals. HIE networks have been established and promoted to facilitate timely information sharing across hospitals. Similarly, hospitals that are part of the same IDS franchise (e.g., Kaiser hospitals) can share information as they have higher interoperability. Additionally, the hospitals that are in the same IDS would have less privacy and competition concerns and therefore lower barriers to sharing of patient data and less data locking.

Although more efficient communication and care coordination are expected via HIEs, better record keeping and retrieval with EHR could still potentially enable availability of patient information to neighboring hospitals even in the absence of HIE or IDS. EHR can create externalities because information sharing is possible between two systems of the same vendor (such as Epic or Cerner). Government is also pushing hard on interoperability across EHR vendors. Patients can always request information to be shared, and the presence of EHR makes such indirect information sharing through patients easier due to ease of data retrieval and more detailed patient health data. Printing and faxing of discharge summaries and information exchange between physicians involved in referrals can also facilitate information exchange between providers (Kripalani et al. 2007), albeit at a lower rate. Overall, we expect EHR by itself to create spillovers and the factors that reduce information sharing barriers, such as HIE and IDS networks, to significantly boost these spillovers.

In sum, while empirical studies on EHR adoption impacts have focused on hospital-level effects, we expect that information and patient sharing provide a linkage among hospitals and create significant EHR spillover effects among these connected hospitals. Thus, we argue that it is important to take a regional or network perspective to understand the real impact of EHR adoption on healthcare costs.

3. Data

We obtained hospital-level EHR adoption from the Healthcare Information and Management Systems Society (HIMSS) database. The longitudinal database contains information on hardware and software adoption of healthcare providers across the nation. Even though HIMSS data have limitations, it remains the most representative and detailed database for health IT adoption in the United States and is used in several studies (e.g., (Miller and Tucker 2011, Dranove et al.

2014, Parente and McCullough 2009, McCullough et al. 2016). We use operational cost data of hospitals from the Medicare Cost Reports database. We obtain other hospital-level characteristics, such as number of discharges, from Medicare data. We merge HIMSS data with Medicare data to construct a hospital-level panel between 1998 and 2012.[1]

To measure the spillover effects, we consider hospitals that are in the same Hospital Service Area (HSA) as a network. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area.[2] An HSA can be a county, a large metropolitan city, or some other geographical unit that meets the HSA criteria. We choose HSA as a network because it is the most granular, well-defined local healthcare market, which is relatively self-contained with respect to hospital care. Cross-hospital externalities can exist beyond an HSA, and our research does not exclude the possibility that spillovers can go beyond a certain regional level. Since HSA is the smallest meaningful market for hospital care, and information and patient sharing can occur beyond HSAs, we can expect the overall spillover effects to be stronger when measurement is not limited to an HSA. We conducted robustness checks using hospital referral regions and counties to measure the spillovers, and our results remain qualitatively similar. Since our focus is on the regional spillover effects from EHR adoption, we drop HSAs in which there is only one hospital, as spillovers across hospitals cannot be calculated. This leads to a panel of 1,614 hospitals in 483 HSAs (1998–2012), and an average of 3.3 hospitals per HSA.

We used American Community Survey data of the U.S. Census at the ZIP code level to calculate the HSA-level demographic characteristics that might affect the healthcare costs such as age, income, and education. We first matched the ZIP codes to the HSAs and then calculated the average statistics for each HSA, weighted by ZIP codes' population. We also used other county- and state-level characteristics that cannot be obtained at the HSA level. The complementary regional resources are shown to be important factors in how hospitals benefit from EHR adoption (Dranove et al. 2014). To proxy for the intensity of the IT resources in the area, we calculated the ratio of high-tech establishments to the total number of establishments in the county using U.S. Census County Business Patterns data (Dranove et al. 2014).[3] At the state level, we used average nurse salaries to control for the labor costs that hospitals face, as nurse salaries is a major component of total labor costs for hospitals.

3.1. Measuring EHR Adoption

There are five main EHR systems that have been used in previous research to capture the EHR capabilities in hospitals: Clinical Data Repository, Clinical Decision Support System, Order Entry, Computerized Physician Order Entry, and Physician Documentation. We identified the adoption of these systems for each hospital-year observation. The Clinical Data Repository (CDR) is a database used by practitioners to maintain up-to-date patient records. These records are often unified across a number of different departments in hospitals. A Clinical Decision Support System (CDSS) helps medical providers in diagnosing patients. Further, this technology can help outlining treatment plans for patients and checking for drug interactions. Order Entry (OE) allows hospitals to streamline operations by replacing paper forms and allowing the electronic transfer of documents. Computerized Physician Order Entry (CPOE) systems enable physicians to enter medical orders that are integrated with other patient information and communicated easily with labs and pharmacy. Physician Documentation (PD) allows physicians to electronically manage patient records. The PD system can then enable practitioners to better assess the validity of their diagnosis and inform doctors about conditions that they may have overlooked. Table 1 provides

Table 1. EHR Systems

EHR systems	Description	1998	2012
Clinical Data Repository (CDR)	Database that is used to maintain an up-to-date record of patients	27%	87%
Clinical Decision Support System (CDSS)	Help medical practitioners with diagnosis and treatment plans	25%	83%
Order Entry (OE)	Allow hospitals to replace paper forms with electronic documents	38%	86%
Computerized Physician Order Entry (CPOE)	Allow physicians to enter medical orders that are incorporated with patient information and communicated with labs and pharmacy	4%	54%
Physician Documentation (PD)	Allow physicians to maintain electronic records about patients' conditions. System can inform doctors about conditions they may have overlooked	9%	46%

descriptions and adoption rates for each technology for the initial and final year of our sample, 1998 and 2012 respectively.

A specific EHR system was considered to be "adopted," if the hospital reported the system's status as "live and operational" in a given year in the HIMSS database. This measure indicates whether the EHR system is in active use; however, we cannot measure the extent and degree of use. For example, we can observe that a hospital is using a CPOE system, but it is not possible to identify how many units in the hospital use the CPOE and for which applications. In other words, the HIMSS database offers a binary measure of EHR use for each single system. We cautiously label this variable as *EHR adoption*, in line with the previous studies, as we are certain that the hospital has adopted and is actively using the EHR systems to some extent, albeit we cannot measure the extent of use. This is an inevitable limitation of the HIMSS data. The potential value of spillover effects is likely to be realized when the systems are widely used at the hospital. However, this limitation does not create a problem for our findings as we expect our results to be stronger if we could measure "the intensity of use" instead of "adoption." Let us suppose only a percentage of hospitals use EHRs widely in several units and applications after adoption, and our findings are most likely driven by these hospitals. If we can still find a significant average effect for all of the hospitals that have adopted EHR, the average effect would be larger if we could identify the ones that have extensive EHR usage. Adoption (binary use for each system) is not a measure of intensity of usage, but it is a prerequisite, and they move in the same direction. Therefore, our results can be interpreted as the lower bound spillover effects, and inability to observe the level of EHR use is not expected to change our results qualitatively (i.e., sign will be retained). We used the ratio of EHR applications that are live and operational at the hospital to the total number of EHR systems (five systems) as a measure of EHR adoption level. This variable changes between zero and one, one indicating that all of the EHR applications are adopted.

3.2. Operational Costs

We use hospital-level operational costs, which is a common dependent variable in the literature on EHR impacts on healthcare costs (e.g., Hillestad et al. 2005, Agha 2014, Dranove et al. 2014). Operational costs are obtained from Medicare cost reports. We deflate operational costs to adjust for price inflation. Operational costs have seven components and Table 2 describes the different cost categories and their average share in total operational costs in our sample.

3.3. Summary Statistics

Table 3 presents the summary statistics for the dependent variable, main independent variables, and control variables used in the analysis. The mean EHR adoption level is 0.38, meaning, on average, hospitals have around two EHR systems (out of five) in our sample. Average operational cost for a hospital in our sample is \$1.24 million with a standard deviation of \$1.08 million.

4. Empirical Specification and Results

4.1. Empirical Specification

Our main goal is to estimate if, and, how a hospital's operational costs are affected by the EHR adoptions of other hospitals in the same HSA. We use yearly EHR adoption level (between zero and one) as the key independent variable. We measure the regional spillovers at the HSA level by estimating the effects of EHR adoption of the focal hospital, and the average EHR adoption of all hospitals in the HSA except the focal hospital, on the focal hospital's costs. We also cross-validate our results by estimating how the focal hospital's EHR adoption affects other hospitals' costs in the HSA as a robustness test (Section 4.5.5).

Table 2. Operational Cost Categories

Cost category	Description	Percentage (%)
General services	Cost of capital, and other cost centers such as pharmacy, employee benefits, and laundry	46
Ancillary services	Cost of operating rooms, anesthesiology, labs, blood processing, and medical services to patients	25
Inpatient routine services	Costs associated directly with inpatients such as intensive care units	15
Outpatient services	Cost of clinics or emergency centers related to outpatients	6
Nonreimbursable	Cost centers including research and gift, flower, and coffee shop	4
Other reimbursable	Cost of home program dialysis and other durable equipment	2
Special purpose	Cost of lung, kidney, liver and other organ acquisition (including ambulatory surgical center)	2

Table 3. Descriptive Statistics

Variables	Mean	Std. dev.	Observations
Operational cost (in million $)	1.24	1.08	24,210
EHR (between zero and one)	0.38	0.33	24,210
HIE	0.08	0.27	11,298
Urban	0.33	0.47	24,210
Population density (1,000s per sq. mile)	3.99	12.09	24,210
Average distance between hospitals (miles)	6.47	7.06	24,210
Hospital density (10s per sq. mile)	0.22	0.51	24,210
Hospital-level controls			
Number of discharges	7,022	6,613	24,210
Total bed admittance days	34,619	28,517	24,210
Case mix index (CMI)	1.43	0.27	16,545
Outpatient charges (millions $)	1.08	1.35	23,730
HSA-level controls			
Percent 65 years and older	13.01	3.55	24,210
Percent college graduate	28.83	10.63	24,210
Total population (millions)	1.07	1.30	24,210
log(*Median household income*)	53,321	13,566	24,210
Other regional-level controls			
Ratio of IT firms in county	0.03	0.01	24,210
Average nurse salaries in state	65,290	8,793	24,210

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

$$\begin{aligned}\log(Cost)_{i,t} =& \beta_0 + \beta_1 EHR_{i,t} + \beta_2 EHR_{i,t-1} + \beta_3 EHR_{h-i,t} \\ &+ \beta_4 EHR_{h-i,t-1} + \theta X_{i,t} + \delta Z_{h,t} + \phi G_{h-i,t} \\ &+ \alpha_i + \lambda_t + e_{i,t} \qquad (1)\end{aligned}$$

where the dependent variable $\log(Cost)_{i,t}$, is the deflated operating cost of focal hospital i at time t. The first independent variable of interest, $EHR_{i,t}$, is the level of EHR adoption at focal hospital i at time t. Therefore, β_1 measures the effect of EHR adoption of the focal hospital on its own costs. To capture potential lagged effects, we add $EHR_{i,t-1}$, which is the EHR adoption level at hospital i at time $t-1$, and β_2 measures the one year lagged effect of EHR adoption of the focal hospital. We add more lagged EHR adoption variables ($t-2$ and $t-3$) in further specifications.

We estimate the spillovers from the EHR adoption of other hospitals in the same HSA to the costs of the focal hospital i. Our main independent variable of interest is $EHR_{h-i,t}$, which represents the average EHR adoption of other hospitals in the same HSA h except for the focal hospital i. Thus, β_3 estimates the effect of EHR adoption of the neighboring hospitals in the HSA on the costs of focal hospital. Similarly, we add lagged values of this variable to account for spillover effects that might materialize over time. Additionally, we control for several hospital and regional characteristics that might influence the relationship between a hospital's EHR adoption and its own costs, as well as cost spillovers from the neighboring hospitals. X_{it} includes time-variant hospital-level characteristics such as number of discharges and number of bed admittance days. We add case mix index and outpatient charges to control for the level of severity of cases in the hospital in further specifications (Section 4.5.1). Z_{ht} represents HSA level control demographics such as population, age, and education. We have these HSA-level demographic characteristics for one year, and we multiply these values by the time trend following Dranove et al. (2014). We further control for the ratio of high-tech establishments in the county to account for resources that are complementary to health IT, and nurse salaries at the state level to control for labor costs in the region. Additionally, we control for other time-variant characteristics of all other hospitals (except the focal hospital) in the same HSA. $G_{h-i,t}$ represents the characteristics of other hospitals in the HSA h (apart from the focal hospital) at time t, including number of discharges and number of bed admittance days. Hospital fixed effects (α_i) control for time invariant heterogeneity across different hospital characteristics. Year fixed effects (λ_t) control for nation-wide shocks to the economy and healthcare market that are experienced by all hospitals. Finally, e_{it} is the random error, which captures unobserved random factors that may affect healthcare costs. Standard errors are clustered by hospital and year.[4]

4.2. Endogeneity and Identification Strategy

The above section described how we estimate regional spillover effects resulting from EHR adoption. However, the relationship between EHR adoption of the neighboring hospitals and costs of the focal hospital is subject to alternative explanations and endogeneity issues. We test the underlying mechanisms of the cost spillovers by studying how information and patient sharing relate to regional spillovers. Everything else being equal, we expect the regional spillovers to be stronger when information sharing is easier and the likelihood and magnitude of patient sharing is higher (Section 4.4). Besides providing evidence for the mechanisms, we conduct several other analyses to address alternative explanations and other endogeneity issues as detailed below and in Section 4.5.

First, there can be patient self-selection bias: patients with different diseases and complexities can select into hospitals based on their EHR investments. Presence of EHR technologies can be advertised by hospitals, or patients who are aware of this information can select different hospitals in the area accordingly. For example, if a hospital attracts more complicated patients as its EHR adoption level increases, its costs can increase since more complex and severe cases have higher costs of providing care. Thus, surrounding hospitals can be left with less severe and less complicated cases that are easier to treat, which reduces their operational costs. Therefore, EHR investments can potentially change the patient pool for the EHR adopting hospital and also for the neighboring hospitals. This scenario offers an alternative explanation of our results where we find that even though EHR adoption leads to an increase in costs for the adopting hospital, it is associated with a decrease in costs for the surrounding hospitals. We address this endogeneity issue in two ways. First, we control for case mix index (CMI) and outpatient charges to control for the complexity of patients. Second, we directly test whether CMI and outpatient charges for the focal hospital and the neighboring hospitals change after EHR adoption of the focal hospital, and the results show that EHR adoption does not change the patient profile of hospitals (Section 4.5.1).

Second, reverse causality could be an issue if the reduction in focal hospital's costs leads to an increase in EHR adoption of neighboring hospitals. For example, everything else being equal, if one hospital decreases its costs and thus increases profits, the other hospitals in the area might feel pressure and try to compete, and investing in EHR can be one way to do so. We exploit the panel structure of our data and test the relationship between timing of changes in EHR adoption and costs. Our results show that the lead values of neighboring hospitals' EHR adoption (at $t+1$ and $t+2$) are *not* significantly related to the current costs of focal hospital, and this relationship should be significant *if* changes in costs lead to changes in EHR adoption of neighboring hospitals. Combining this with the significant lagged effects of neighboring hospitals' EHR adoption on focal hospital's costs suggests that changes in costs of the focal hospital follow the changes in EHR adoption of neighboring hospital, and not the other way around, thus providing evidence for a causal direction from EHR adoption to cost spillovers (Section 4.5.2).

Third, there can be confounding factors. We used hospital fixed effects to control for the unobserved time-invariant heterogeneity among hospitals. However, there can still be a time-varying confounding factor that affected both EHR adoption and costs of hospitals that is not related to spillovers created through information and patient sharing, and this could have led to a spurious correlation. We conducted a falsification test to address this issue. Since the spillover mechanisms rely on shared information and patients, we do not expect externalities to materialize for hospitals that are located too far from each other for such mechanisms to occur. If significant effects were found between very distant hospitals, it would provide evidence for a spurious correlation. While significant spillover effects are observed for hospitals in the same HSA, no significant spillover effects are found for hospitals that are very distant from each other (East coast versus West coast of the United States). This provides further evidence supporting the relation between information and patient sharing mechanisms and EHR spillover effects (Section 4.5.3).

4.3. Results: Regional Spillover Effects of EHR Adoption

Table 4 presents the results for Equation (1) where we estimated the effects of EHR adoption of the focal hospital on its own operational costs, and the spillover effects from the other hospitals in the HSA. We found that EHR adoption of the focal hospital is associated with higher costs, consistent with other studies that have used HIMSS data (e.g., Dranove et al. 2014). Interestingly, the coefficients of other hospitals' EHR adoption in the HSA excluding the focal hospital are negative and significant, indicating spillover effects from EHR adoption of neighboring hospitals to the focal hospital's costs. This evidence supports the argument that although operational cost increases at the hospital that is making the EHR investment, it can lead to a reduction in the costs of providing care for colocated hospitals. The estimates indicate that adoption of one more EHR system in the focal hospital increases its own costs 1.8% in the current year and 2.3% in four years. If the neighboring hospitals in the same HSA adopt one more EHR, this corresponds to 1% decrease in the costs of the focal hospital in the current year, and a cumulative effect of 1.5% decrease in four years.[5]

4.4. The Mechanisms of Spillover Effects

In Section 4.3, we found significant regional spillovers showing that hospitals' cost can be affected by EHR adoption of other hospitals in the same regional network. In this section, we focus on the mechanisms of information and patient sharing and investigate how they relate to regional spillovers.

4.4.1. Information Sharing. One primary mechanism for the regional spillover effects to occur is information sharing across hospitals. When information on

Table 4. Effects of EHR Adoption of the Focal Hospital and Other Hospitals in the HSA

	DV: log(*Costs of focal hospital*)			
Variables	(1)	(2)	(3)	(4)
Other hospitals EHR	−0.048*** (0.010)	−0.028** (0.012)	−0.029** (0.012)	−0.026** (0.012)
Other hospitals EHR ($t-1$)		−0.025* (0.013)	0.001 (0.014)	0.000 (0.014)
Other hospitals EHR ($t-2$)			−0.041*** (0.013)	−0.016 (0.015)
Other hospitals EHR ($t-3$)				−0.034*** (0.013)
Focal hospital EHR	0.091*** (0.007)	0.061*** (0.008)	0.059*** (0.008)	0.056*** (0.008)
Focal hospital EHR ($t-1$)		0.041*** (0.009)	0.014 (0.009)	0.012 (0.009)
Focal hospital EHR ($t-2$)			0.037*** (0.008)	0.014 (0.009)
Focal hospital EHR ($t-3$)				0.031*** (0.009)
Hospital-level controls				
log(*Number of discharges*)	0.151*** (0.017)	0.154*** (0.018)	0.156*** (0.019)	0.161*** (0.020)
log(*Bed admittance days*)	0.324*** (0.029)	0.313*** (0.031)	0.298*** (0.033)	0.289*** (0.035)
HSA-level controls				
Percent 65 *years and older* × *Year*	0.042 (0.133)	0.103 (0.146)	0.070 (0.156)	−0.025 (0.171)
Percent college graduate × *Year*	−0.046 (0.047)	−0.028 (0.050)	−0.011 (0.054)	0.015 (0.060)
log(*Total population*) × *Year*	−1.295*** (0.321)	−1.178*** (0.341)	−0.975*** (0.368)	−0.948** (0.402)
log(*Median household income*) × *Year*	2.678 (1.896)	1.258 (2.018)	0.469 (2.155)	−0.757 (2.414)
Other regional-level controls				
Ratio of IT firms in the county	1.657*** (0.595)	1.759*** (0.639)	1.053 (0.682)	1.310* (0.784)
log(*Average nurse salaries in state*)	0.325*** (0.059)	0.322*** (0.063)	0.299*** (0.063)	0.299*** (0.067)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	24,210	22,596	20,982	19,368
Adj. R-squared	0.564	0.538	0.507	0.478

Notes. Standard errors (in parentheses) are two-way clustered by hospital and year.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

shared patients can be exchanged efficiently across hospitals, this timely patient information from other hospitals can allow a hospital to reduce unnecessary tests and provide more proper and coordinated care to patients. If this argument holds, we should observe regional spillover effects to be stronger when information sharing is more viable in the area. While EHR by itself makes it easier to share information due to better records and easier retrieval of information, patient information can be shared much more easily and rapidly when hospitals adopt HIEs or belong to same IDS franchise. We therefore utilize the variations in HIE and IDS memberships to test the information-sharing mechanism.

Health Information Exchanges. Health information exchanges are networks that are specifically designed for enabling information sharing among the participating hospitals. Even though the existence of an HIE does not guarantee that the hospitals are sharing information seamlessly, it is reasonable to assume that it would increase the likelihood of timely sharing of information across hospitals. Table 5 presents the results where we analyze the role of the HIE in regional spillovers. As HIE information is only available after 2005 in the HIMSS database, we have to limit our analysis to years 2006–2012. We use the HIE information in two ways. First, we test how EHR spillovers differ by whether hospitals are in an HIE or not.[6] In column (1), we decom-

Table 5. Spillover Effects by HIE

	DV: log(*Costs of focal hospital*)			
Variables	(1)	(2)	(3)	(4)
Other hospitals EHR in HIE	−0.022***	−0.020***		
	(0.004)	(0.004)		
Other hospitals EHR outside HIE	−0.008***	−0.008***		
	(0.003)	(0.003)		
Other hospitals EHR in HIE × *Focal hospital HIE*		−0.013*		
		(0.007)		
Other hospitals EHR outside HIE × *Focal hospital HIE*		0.003		
		(0.002)		
Other hospitals HIE			−0.041***	−0.026***
			(0.010)	(0.010)
Other hospitals HIE × *Focal hospital HIE*				−0.145***
				(0.036)
Focal hospital EHR	0.042***	0.043***	0.042***	0.042***
	(0.008)	(0.008)	(0.008)	(0.008)
Focal hospital HIE	0.014*	0.016*	0.012*	0.033***
	(0.008)	(0.009)	(0.008)	(0.008)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	11,298	11,298	11,298	11,298
Adj. R-squared	0.343	0.343	0.343	0.341

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

$^{*}p < 0.1$; $^{***}p < 0.01$.

pose the spillover measure *Other hospitals EHR adoption* into two parts: EHR adoption of hospitals that are in an HIE and EHR adoption of hospitals that are not in an HIE. The coefficients of the two variables would reveal if the cost spillovers from hospitals that are in an HIE are different than those that are not in an HIE, controlling for the level of EHR adoption. Significant spillovers are observed from the EHR adoption by both hospitals that are in an HIE and outside of an HIE, but the EHR spillovers driven by the HIE hospitals are statistically stronger than the non-HIE hospitals. These results suggest that EHR create spillover effects by themselves because EHR enhance record keeping and make data retrieval easier and faster. The HIE, on the other hand, significantly increases the spillover effects due to potentially lower barriers of information sharing. Since information exchange is the easiest when both the focal and neighboring hospitals have an HIE, we add interactions between the EHR spillover terms and focal hospital's HIE adoption in column (2). We find that additional EHR spillovers from HIE hospitals are observed when the focal hospital is also in HIE.

Second, we test the spillover effects from the HIE adoption directly. In column (3) of Table 5, we find that the neighboring hospitals' HIE adoption is negatively associated with focal hospital's costs, providing consistent support to the connection between information sharing mechanism and regional spillovers. Similarly, we interact the focal hospital's and neighboring hospitals' HIE in column (4) of Table 5, and find the interaction term to be significant and negative, supporting that the spillovers are stronger when focal and neighboring hospitals mutually adopt a HIE. Overall, these results provide evidence that information sharing plays an important role in driving the regional spillover effects.

Integrated Delivery Systems. Besides the HIE, it is also easier to share information for the hospitals that are in the same integrated delivery system (IDS). An IDS is a network of hospitals under a parent holding company, and their EHR systems tend to be more compatible with higher data interoperability; therefore, these hospitals can still share information easily without the presence of an HIE. Additionally, hospitals that are part of the same franchise might have lower data-sharing restrictions and data locking because the privacy and competition concerns for sharing data among the hospitals under the same franchise network would be lower. Therefore, membership in an IDS also provides a test of the information-sharing mechanism for the regional spillovers. We conduct this test by decomposing the spillovers driven by hospitals that are in

Table 6. Spillover Effects by IDS

	DV: log(*Costs of focal hospital*)			
Variables	(1)	(2)	(3)	(4)
Other hospitals EHR in IDS	−0.017**	−0.035***		
	(0.007)	(0.012)		
Other hospitals EHR in IDS ($t-1$)		−0.001		
		(0.009)		
Other hospitals EHR in IDS ($t-2$)		−0.002		
		(0.009)		
Other hospitals EHR in IDS ($t-3$)		−0.012		
		(0.008)		
Other hospitals EHR outside IDS	−0.002	0.003		
	(0.002)	(0.003)		
Other hospitals EHR outside IDS ($t-1$)		−0.006**		
		(0.003)		
Other hospitals EHR outside IDS ($t-2$)		0.005		
		(0.004)		
Other hospitals EHR outside IDS ($t-3$)		−0.007**		
		(0.003)		
Other hospitals HIE in IDS			−0.044***	−0.045***
			(0.013)	(0.017)
Other hospitals HIE in IDS ($t-1$)				0.012
				(0.011)
Other hospitals HIE in IDS ($t-2$)				−0.050***
				(0.015)
Other hospitals HIE in IDS ($t-3$)				−0.024**
				(0.011)
Other hospitals HIE outside IDS			−0.014***	−0.009*
			(0.003)	(0.005)
Other hospitals HIE outside IDS ($t-1$)				−0.004
				(0.005)
Other hospitals HIE outside IDS ($t-2$)				−0.006
				(0.005)
Other hospitals HIE outside IDS ($t-3$)				−0.013**
				(0.005)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	11,298	6,456	11,298	6,456
Adj. R-squared	0.341	0.235	0.343	0.237

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the same IDS as the focal hospital versus the hospitals that are not in the same IDS. In this case, we can directly identify which IDS the hospitals are in and all of the other hospitals in the HSA that belong to the same IDS. Columns (1) and (2) of Table 6 show that the EHR spillovers from the hospitals that are in the same IDS as the focal hospital are stronger. Similarly, HIE spillovers driven by the hospitals that are in the same IDS franchise are statistically larger (columns (3) and (4) of Table 6). Overall, our findings support the role of any type of information-sharing network (HIE or IDS) in magnifying regional spillovers.

Spillover Effects on Different Cost Categories. We expect the spillovers due to information sharing to reflect in the cost categories that involve direct patient care; therefore, we analyze the spillover effects of EHR adoption on different cost categories (Table 2) to provide further evidence on the mechanisms. If information sharing improves care coordination and decreases redundant tests and procedures, we anticipate seeing EHR spillover effects in general services costs (includes equipment costs), ancillary services costs (includes laboratory, tests, imaging, and medical services-associated costs), and inpatient and outpatient services costs. On the other hand, we would not expect any spillover effects on nonreimbursable costs, which include costs on research and on gift and coffee shops.

We decompose the total cost into its seven components and test whether each of these cost categories of the focal hospital is affected by the EHR adoption of neighboring hospitals in the same HSA, and the results are reported in Table 7. We find that there are signifi-

Table 7. Spillover Effects by Cost Categories

	DV: log(*Cost category of focal hospital*)						
	(1) General	(2) Ancillary	(3) Inpatient	(4) Outpatient	(5) Nonreimbursable	(6) Other reimbursable	(7) Special purpose
Other hospitals EHR	−0.041***	−0.048***	−0.038***	−0.207***	−0.030	−0.036	−0.209***
	(0.012)	(0.015)	(0.011)	(0.032)	(0.075)	(0.052)	(0.072)
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,210	23,955	24,195	20,775	14,100	20,460	21,195

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.
***$p < 0.01$.

cant spillovers on the cost components of general services, ancillary services, and inpatient and outpatient services that can benefit from information sharing and coordination of care, while the coefficients on nonreimbursable costs are not significant. These results provide evidence on the sources of cost reductions via EHR spillovers. Significant spillover effects on patient services-related costs such as costs of tests, imaging, medical procedures, and inpatient and outpatient services suggest that externalities are attributable to information sharing.

4.4.2. Patient Sharing. In the previous subsection, we showed that the spillover effects are shaped by how easy it is for hospitals to share information. Information sharing is needed when patients transfer between hospitals. Therefore, the underlying driver for the regional spillover effects is shared patients among hospitals, and if this speculation is true, then spillover effects should be stronger when there are more shared patients. Our data cover the whole of the United States and use public data sources, and therefore it is not feasible to have direct information on exact numbers of patients shared among all hospitals at this scale. However, we test the premise of patient sharing using regional characteristics that likely affect the number of shared patients.

Suppose the total number of patients in a location is n and the probability of patients to move across hospitals is p, and then the expected number of shared patients s can be approximated by $s = n * p$. Therefore, any regional characteristic that is associated with higher n or higher p should strengthen the regional spillovers from EHR investments. For example, urban locations have higher population density (i.e., higher n), and they also tend to have multiple hospitals colocated, and therefore the chances for patients to move across hospitals are also higher (i.e., higher p). Moreover, when hospitals are more closely located, it is easier for patients to travel to different hospitals; therefore, patient sharing among these hospitals is more likely (i.e., higher p). We utilize four regional characteristics related to patient and hospital concentration, (1) urban versus rural HSAs, (2) population density (population per square mile), (3) average distance between hospitals in the area, and (4) hospital density (number of hospitals per square mile), to proxy for patient sharing and study if regional spillovers differ by these characteristics.

First, we test whether the spillover effects are different in urban versus rural HSAs by interacting the neighboring hospitals' EHR adoption with an Urban HSA dummy (column (1) of Table 8).[7] Therefore, the baseline coefficient of *Other hospitals EHR* represents the spillover effects in rural areas. The interaction term between *Other hospitals EHR* and the dummy variable *Urban* represents the difference in spillovers in urban areas compared to rural areas. We find that there are significant EHR spillovers in both rural and urban areas, and that these spillovers are stronger in urban locations than in rural locations.

Second, higher population density (higher n in an area) could also lead to a higher number of shared patients and therefore result in stronger EHR spillovers. We utilize population density measure (population divided by total area of the HSA) in column (2) of Table 8, and we find that EHR spillovers are stronger in areas with higher population density.

Next, we use distance between hospitals in the region as a proxy for the likelihood of patient sharing. When hospitals are closer to each other in the HSA, we expect more patient sharing to occur among them, as it would be easier for patients to visit different hospitals given their proximity and lower transportation costs (i.e., higher p). We calculate the pairwise distances between the hospitals in the HSA based on their latitudes and longitudes, and then average these distances. The median distance between hospitals in HSAs is 4.92 miles; accordingly, we create a

Table 8. Spillover Effects by Patient and Hospital Concentration

DV: log(*Costs of focal hospital*)				
Variables	(1)	(2)	(3)	(4)
Other hospitals EHR × Urban	−0.070***			
	(0.020)			
Other hospitals EHR × Population density		−0.008***		
		(0.001)		
Other hospitals EHR × Distance less than five miles			−0.059***	
			(0.018)	
Other hospitals EHR × Hospital density				−0.208***
				(0.031)
Other hospitals EHR	−0.034***	−0.030***	−0.010	−0.016
	(0.010)	(0.010)	(0.016)	(0.010)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	24,210	24,210	24,210	24,210
Adj. R-squared	0.564	0.560	0.564	0.561

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

$^{***}p < 0.01$.

dummy variable that takes the value of one if the average distance among hospitals in the HSA is less than five miles.[8] We use this dummy variable to test if spillover effects are significantly different between the HSAs with shorter distance among hospitals and the HSAs with longer distance among hospitals. Column (3) of Table 8 presents the results where we interact the neighboring hospitals' EHR adoption with the distance dummy. We find stronger spillover effects in the HSAs where hospitals are more closely located (i.e., average distance less than five miles). Interestingly, spillover effects are not statistically significant if the average distance among the hospitals in the HSA is greater than five miles, suggesting that travel distance is an important factor that shapes up spillover effects because it is less likely to have a significant number of patients moving across hospitals when they are far apart.

In column (4) of Table 8, we test whether EHR spillovers are stronger in areas with higher hospital density, which is calculated as number of hospitals divided by total area of the HSA. Again, patients are more likely to be shared when there are more hospitals per square mile. We find consistent result that spillovers are stronger for HSAs with higher hospital density.

In sum, these findings provide evidence supporting the role of patient sharing in driving regional externalities and indicate that shared patients create the link among hospitals and facilitate spillovers.

4.5. Additional Analyses and Tests

We argue that information and patient sharing drive spillover effects, and our results have provided evidence supporting that spillover effects are stronger in areas where information sharing among hospitals is easier and hospitals are more likely to share patients, after controlling for many time-invariant and -variant factors. To further validate our main results and to address endogeneity issues that are discussed in detail in Section 4.2, we performed several additional analyses.

4.5.1. Alternative Explanation: Addressing Patient Selection. If more complex patients select into hospitals that have higher EHR investments, the rest of the hospitals in the area might remain with a less costly patient pool. This explanation is consistent with our findings that EHR is associated with higher costs for the adopting hospital and lower costs for the surrounding hospitals. To address this endogeneity issue, first, we control for the case mix index (CMI) that measures the overall complexity of patients in a hospital. Patients that have the same conditions, complexity and needs are assigned into groups, which are known as diagnosis-related groups (DRGs). A hospital's CMI is calculated as the average of its DRGs. This value represents the clinical complexity of all patients in the hospital, and a higher CMI indicates more severe patient population. Ideally, we would have liked to include CMI in our main analysis, but the CMI variable is missing for several hospitals. Since we are conducting regional-level calculations, it is important to maintain a good representation of hospitals in HSAs. Therefore, we add CMI

Table 9. Effect of EHR Adoption on Complexity of Patients

DV:	(1) CMI of focal hospital i	(2) CMI of other hospitals in HSA $h-i$	(3) Outpatient charges of the focal hospital i	(4) Outpatient charges of other hospitals in the HSA $h-i$
Focal hospital EHR	−0.012***	0.005	0.022	−0.005
	(0.005)	(0.004)	(0.015)	(0.009)
Focal hospital EHR $(t-1)$	0.002	0.001	−0.014	0.012
	(0.005)	(0.004)	(0.020)	(0.011)
Focal hospital EHR $(t-2)$	−0.007	−0.004	0.009	−0.009
	(0.005)	(0.004)	(0.015)	(0.012)
Focal hospital EHR $(t-3)$	−0.005	0.000	0.002	0.000
	(0.006)	(0.005)	(0.015)	(0.013)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	10,417	10,417	10,417	10,417
Adj. R-squared	0.225	0.333	0.812	0.706

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

***$p < 0.01$.

in our analysis as a robustness check. In the specifications where we control for focal hospitals' and surrounding hospitals' CMI, we find similar results. This finding provides evidence that CMI is not driving the cost differences after EHR adoption.

Second, and as a more direct test of this alternative explanation of patient selection, we test whether EHR adoption affects the CMI of the focal hospital and surrounding hospitals. Specifically, we want to know if EHR adoption leads to an increase in CMI in the focal hospital and decrease in CMI in the surrounding hospitals. In column (1) of Table 9, the dependent variable is CMI of the focal hospital. We found a slight negative relationship between EHR adoption of the focal hospital and its own CMI; however, this finding works against the alternative explanation and therefore strengthens our results. That is, the increase in costs after EHR adoption for the focal hospital cannot be due to more severe and complicated patient cases because CMI index does not increase after EHR adoption. This alternative explanation is further invalidated in results shown in column (2) of Table 9, where we did not find a significant relationship between CMI of neighboring hospitals and EHR adoption of the focal hospital.

The CMI measure focuses on the composition and complexity of the inpatients, and we conduct similar exercises using outpatient charges, which can be an alternative proxy for the complexity of the patients treated by the hospital. When we control for outpatient charges, our results remained similar. In columns (3) and (4) of Table 9, we did not find significant relationships between EHR adoption and outpatient charges of the focal hospital and the neighboring hospitals. These findings are in line with the Adler-Milstein and Jha (2014) study that found that the complexity of patients and payment per discharge were the same between EHR adopters and nonadopters. Overall, we find evidence that EHR adoption does not affect the patient complexity for the adopting hospital and the neighboring hospitals.

4.5.2. Timing of Changes in EHR Adoption and Costs: Addressing Reverse Causality. Reverse causality would be an issue if hospitals' EHR adoption is affected by the costs of other hospitals, and to be consistent with the observed findings, a reverse causality explanation would suggest that a decrease in focal hospitals' costs causes an increase in EHR adoption by other hospitals in the HSA. In other words, if reverse causality holds, there should be a significant relationship between focal hospital's current costs and other hospitals' future EHR adoption. To test for the plausibility of this explanation, we analyze if the leads of EHR adoption are significantly associated with the current cost levels. If there is such significant relationship, this would provide evidence for reverse causality.

Table 10 presents the results where we include the one- and two-year leads of the neighboring hospitals' EHR adoption, and we find that these terms are not statistically significantly correlated with the costs of the focal hospital and are small in magnitude. These results combined with our earlier analysis in Section 4.3 support a causal direction from EHR adoption to cost spillovers, since the changes in costs are realized after changes in neighboring hospitals' EHR adoption, and not vice versa.

Table 10. Lead EHR Adoption and Spillover Effects

DV: log(*Costs of focal hospital*)				
Variables	(1)	(2)	(3)	(4)
Other hospitals EHR ($t+1$)	0.008 (0.011)	−0.006 (0.013)	−0.006 (0.012)	−0.008 (0.013)
Other hospitals EHR ($t+2$)		0.011 (0.011)	−0.011 (0.012)	−0.006 (0.012)
Other hospitals EHR	−0.053*** (0.012)	−0.038*** (0.014)	−0.042*** (0.014)	−0.040*** (0.014)
Other hospitals EHR ($t-1$)		−0.016 (0.014)	0.005 (0.015)	0.005 (0.015)
Other hospitals EHR ($t-2$)			−0.033** (0.013)	−0.013 (0.016)
Other hospitals EHR ($t-3$)				−0.027* (0.014)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	22,596	20,982	19,368	17,754
Adj. R-squared	0.594	0.572	0.546	0.546

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11. Spillover Effects Among Distant Hospitals

DV: log(*Costs of focal hospital*)				
Variables	(1)	(2)	(3)	(4)
Other hospitals EHR	−0.010 (0.018)	−0.019 (0.020)	−0.026 (0.019)	−0.020 (0.019)
Other hospitals EHR ($t-1$)		0.011 (0.020)	0.011 (0.023)	0.000 (0.022)
Other hospitals EHR ($t-2$)			0.008 (0.021)	0.026 (0.023)
Other hospitals EHR ($t-3$)				0.000 (0.024)
Hospital fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	9,195	8,582	7,969	6,743
Adj. R-squared	0.390	0.361	0.327	0.224

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

4.5.3. Falsification Test: Addressing Spurious Correlation. The findings can be driven by unobserved factors or coincidence, leading to a spurious correlation. Hospitals need to be connected via shared information and patients for EHR spillovers to materialize. We conduct a falsification test and analyze the relationship between hospitals that do not draw patients from the same pool (i.e., the likelihood of sharing information and patients is negligible). We do not expect to observe any spillover effects among distant hospitals, as it is not likely that the extent of information and patient sharing would be large enough to create significant spillover effects between them. In Table 11, we analyze the relationship between EHR adoption and costs of hospitals located on the east and west coasts of the United States. We matched each hospital located on the east coast to a randomly selected HSA on the west coast (and vice versa). We do not find any significant relationship between the EHR adoption and costs of hospitals that are located on the other side of the country, providing assurance that information and patient sharing is critical to the observed spillovers, and that the findings are not due to a spurious correlation.

4.5.4. Additional Results: Spillover Effects Before and After HITECH. The HITECH Act, which was announced in 2009, provides incentives and financial subsidies for hospitals to adopt EHR and achieve meaningful use of these systems. Although implementation of HITECH started in 2012, we expect the announcement to have an effect on hospitals' EHR investment plans. This "exogenous shock" in the form of policy announcement can change the magnitude of spillover effects that were observed prior to HITECH and can provide additional evidence on the relationship between EHR and regional spillover effects. Specifically, following the announcement of HITECH, hospitals started investing in EHR significantly and using them more widely and intensively within the hospital; therefore, we expect the regional spillovers to be stronger in recent years.

We created a HITECH dummy that takes the value of one if the year is 2009 or later. Then we interacted this variable with the other hospitals' EHR adoption, which allows us to test whether the spillovers before and after HITECH years are statistically different. The results from Table 12 show that significant spillover effects exist prior to the announcement of the HITECH Act; moreover, the spillover effects are significantly stronger after HITECH. This increase in spillover effects is expected to occur with increase in EHR adoption and use levels by hospitals. Overall, this result confirms that as neighboring hospitals increase their EHR adoption and use levels, regional spillover effects increase.

4.5.5. Additional Robustness Checks. The first robustness check we conducted was to use different regional units to calculate the spillover effects.[9] We selected HSA for our main analysis since it is the most granular and well-defined healthcare market, but spillovers can manifest themselves through patient

Table 12. Spillover Effects Before and After HITECH

DV: log(*Costs of focal hospital*)		
Variables	(1)	(2)
Other hospitals EHR × *Post HITECH*	−0.023***	0.026
	(0.007)	(0.021)
Other hospitals EHR $(t-1)$ × *Post HITECH*		−0.052**
		(0.022)
Other hospitals EHR	−0.034***	−0.038**
	(0.010)	(0.015)
Other hospitals EHR $(t-1)$		0.001
		(0.016)
Hospital fixed effects	Yes	Yes
Year fixed effects	No	No
Observations	24,210	22,596
Adj. R-squared	0.560	0.533

Notes. Hospital-level controls for the focal hospital and for the other hospitals in the HSA: log(*Number of discharges*), log(*Bed admittance days*), *EHR adoption*. HSA-level controls: *Percent residents 65 years and older*, *Percent high school graduate*, *Percent college graduate*, log(*Total population*), log(*Median household income*). Other regional-level controls: *Ratio of IT firms in the county*, log(*Average nurse salaries in state*). Standard errors (in parentheses) are two-way clustered by hospital and year.

$^{**}p < 0.05$; $^{***}p < 0.01$.

mobility that can certainly exceed an HSA. We conducted analysis to estimate the spillover effects at the (a) hospital referral region level and (b) county level, and our results remained similar.

Second, we checked the robustness of our results by creating a weighted regional EHR adoption measure by each hospital's share of admissions and discharges in the HSA, since EHR adoption of hospitals with larger volume of patients would matter more in creating regional spillovers. Our results remain robust to weighting the neighboring hospitals' EHR either by their admissions or discharges.

Third, we checked the robustness of our results with different treatments of missing observations of the operational cost variable. Since our main goal was to estimate a regional spillover effect and not hospital-level effects, we had to find a balance between having a good regional representation of hospitals and the treatment of missing values. Dropping all hospitals with any missing values would not have allowed us to achieve a good regional representation. In our main analysis, we allowed at most three years of missing observations in the 15-year panel, to have a good representation of the hospitals in the HSAs. We repeated our analysis by using different methods or different cutoffs for the missing value, and our results remain robust. This further assures that the results are not driven by treatment of missing values, and we are confident about the significant spillover effects that are created by EHR adoption.

Fourth, we differentiated between basic EHR and advanced EHR systems to test whether a certain type of EHR drives the spillovers. HIMSS (2011) groups Clinical Data Repository, Clinical Decision Support System, and Order Entry into the basic EHR category, and Computerized Physician Order Entry and Physician Documentation into the Advanced EHR category. Theoretically, either basic or advanced EHR systems can create spillover effects with the proposed mechanisms of coordination and efficiency spillovers via information and patient sharing. We found that both basic and advanced EHR systems are associated with regional spillovers, and their effects are not statistically different from each other.

Finally, we cross-checked our findings by employing an alternative empirical specification where we use the focal hospital's EHR adoption as the main independent variable and the neighboring hospitals' costs except the focal hospital as the dependent variable. We find significant spillovers from the focal hospital's EHR adoption to the neighboring hospitals' costs in this specification, consistent with the main findings.

5. Discussion

5.1. Key Findings

The goal of this research is to theorize and estimate the degree of externality (spillover effect) that EHR adoption has on a regional network of hospitals. Information and patient sharing among hospitals in the same network provide mechanisms that could drive regional externalities. Understanding these spillover effects helps shed light on whether EHR adoption leads to reductions in healthcare costs at the macro level. We found evidence for positive regional externalities of EHR adoption, as it is associated with a decrease in the costs of the neighboring hospitals.[10] Moreover, having more hospitals in HIE and IDS networks in a region strengthens the EHR spillovers, providing evidence for the information sharing mechanism in creating spillovers. We also find evidence that the spillover effects are stronger in areas with higher population and hospital density, supporting that spillovers are related to patient sharing.

5.2. Implications for Research and Policy

We contribute to several streams of literature. First, our study relates to the literature on the economic impacts of health IT. Most of the preexisting EHR research focuses on the hospital-level outcomes. Additionally, empirical evidence based on hospital-level analyses of the impacts of EHR adoption on healthcare costs is mixed (Jones et al. 2012). We propose that regional-level analysis can provide a societal perspective to gain insights on macroeconomic impacts of EHR adoption, and reconcile the mixed hospital-level findings on EHR adoption impacts on healthcare costs. Integrating the IT productivity spillovers and hospital network literatures, we theorize that EHR adoption of hospitals can affect costs of the neighboring hospitals through shared information and patients, and such spillover effects were empirically quantified in this study. Additionally, we extend the general literature on IT productivity and value by showing how IT can create spillover effects beyond the investing organization in the context of health IT investments.

Healthcare and medical literatures report that healthcare resources and outcomes are highly localized and vary significantly across regions. Quality and cost variables are often measured and analyzed at the county, city, state, and country levels in health policy and medicine studies (e.g., Fisher et al. 2009, Lewis 1969, McPherson et al. 1981, Welch et al. 1993). These literatures have documented significant variations in healthcare delivery and costs across regions and have attempted to understand the factors affecting these local variations (e.g., Adler-Milstein et al. 2009, Wennberg and Gittelsohn 1973, Wennberg and Fowler 1977, Wennberg 1984). Research initiatives combining data from several sources provide information on how healthcare resources are distributed within the United States, such as the Dartmouth Atlas of Health Care. This regional healthcare map clearly indicates that healthcare resources are highly localized in the United States. Given the nature of the healthcare system, and the focus of government policies, we believe it is important to integrate this regional perspective into the economic impacts of health IT research. Even though several studies mention potential regional externalities, not many of them provide theory and evidence regarding the regional or network impacts. We are also not aware of any empirical research trying to quantify the level of EHR externalities. We aim to contribute to the literature by providing theoretical arguments and empirical evidence on the spillover effects of EHR adoption by integrating regional health economics, network externalities, and health IT literatures.

The results have a number of important public policy implications. Healthcare costs remain to be one of the most important policy challenges in the United States. Health IT has also taken a significant role in U.S. healthcare policy, and it has been subject to a big debate. The HITECH Act devotes around $19 billion to provide incentives to healthcare providers for EHR adoption, and there have been ongoing discussions among policy makers whether the benefits of EHR investments compensate for the costs. The mixed findings on the impacts of EHR adoption on healthcare costs increase the skepticism about the perception that EHR is a means to reduce healthcare costs.

If there are positive externalities of EHR adoption in a network, hospital-level studies can understate the societal impacts of such health IT investments. We provide evidence that EHR adoption is associated with higher costs for the adopting hospital, but its cost benefits can accrue in other hospitals in the same HSA by improving care coordination. Altogether, there is an aggregate cost reduction at the society level resulting from EHR adoption. Since the regional- or network-level effects of EHR adoption can differ from hospital-level effects, policy makers can provide incentives for hospitals that are designed to achieve an optimal outcome for the region. The findings indicate that policy makers should account for the potential externalities and consider that expected benefits could be realized in other colocated hospitals, especially as the data interoperability and ease of information sharing increases among hospitals.

5.3. Implications for Managers

Our results have implications for hospital managers and operators' decision making. Our findings emphasize the value of coordinating hospitals' investment decisions on their information infrastructures as well as health data interoperability. It is important that hospital managers and operators know that they actually gain benefits, as opposed to losing benefits, from such coordination efforts, and ensuring information sharing among hospitals will produce a win–win–win situation for investing hospitals, other hospitals, and patients. However, it is important to note that this argument is contingent on the value-based system that the U.S. healthcare system is transitioning into rather than a fee-for-service model.[11]

There are several barriers to information sharing, such as competition concerns between IDSs, difficulty of transferring data between EHR systems of different vendors, and an inadequate level of sophistication and maturing of the HIE. These issues make coordination efforts among the hospitals even more critical for the realization of cost-saving benefits in health networks. The hospitals that are in the same HIE and IDS can coordinate together to ensure that their health IT systems are compatible and data are interoperable to facilitate better care coordination. Additionally, the hospital managers can develop mechanisms to ensure that the data is not locked and can be shared easily within the network.

Moreover, the spillover effects increase with more shared patients among hospitals. Therefore, as a start, hospital managers and operators should know which other hospitals they share more patients or expect to share patients with in the future, since it would be beneficial to adopt compatible technologies with those hospitals. When it comes to new investments, it will help to coordinate decisions among the hospitals in the same network or that have high patient sharing. When patients are shared in both directions (from hospital A to B and from B to A), coordination can be easier. However, when patient sharing occurs only in one direction (say from hospital A to B, but not from B to A), coordination can be more difficult. In that case, it can make sense for hospital B to subsidize A to ensure efficient information sharing and data interoperability. We also note that the idea of externalities can also apply beyond EHR investments and could extend to other mechanisms that facilitate information sharing and care coordination among the hospitals.

In addition to providing implications for hospital managers and operator's decision making, our results also provide some strategic insights to managers in other industries. Our results highlight that information exchange and shared customers could drive spillovers among companies that offer complementary products or services. Particularly, investment by one company could potentially affect other companies that share customers and engage in information exchange with the investing company. For example, information on shared customers about their preferences and behaviors could potentially enable better offerings or services to these shared customers by another company.

5.4. Limitations and Future Research

Our study argues that one hospital's EHR investment decision can affect the other hospitals' costs of caring for patients because of shared patients and their information. While we were unable to obtain data on the number of patients shared across hospitals at the national level and had to rely on proxies for patient sharing, direct information on number of shared patients could be possible to obtain for a smaller geographical unit, such as a particular state. Future research can explore the magnitudes of different spillover mechanisms with such data, which would have important public policy implications. Moreover, we are not able to observe the extent and intensity of EHR use in the hospitals and therefore identify the regional spillover effects based on the EHR adoption measure (that captures active use without measuring the intensity of use at the hospital) in the HIMSS data. We expect the results to be stronger if the extent of EHR usage at the hospitals can be observed instead of EHR adoption; therefore, we interpret our findings as the lower bound of potential health IT spillovers. Our results exploiting the timing of the announcement of HITECH support stronger spillover effects following HITECH, which arguably could be due to more intensive use of EHR in hospitals. Data on extent of EHR use across different departments and applications in hospitals can enable more accurate estimation of the spillover effects.

Spillover effects may also be created through vendor efficiency, which can translate into lower EHR implementation and maintenance costs for hospitals. For example, as more hospitals adopt EHR systems, vendors may gain efficiency and charge less. We do not have data on the costs of EHR implementation for each hospital to directly test this mechanism. However, vendor efficiency does not appear to drive our observed results. If this argument holds, we would expect to find spillovers among distant hospitals as well because large vendors can build knowledge and efficiency via implementations in similar hospitals that are not colocated. However, we find that EHR spillovers do not extend to distant hospitals (Table 11). We also find that hospitals that do not change their EHR investment levels can also gain benefits when their neighboring hospitals adopt more EHR systems. These findings suggest that information and patient sharing mechanisms are essential for EHR spillovers. Additionally, we find that there are significant spillovers in tests, imaging, laboratory, and inpatient and outpatient services costs, indicating that regional spillover effects are related to patient services and go beyond EHR implementation costs (Table 7). Even though the vendor efficiency explanation cannot fully account for our observed results on regional spillovers, it suggests that late adopters may benefit more, at least at the national scale. This would imply that timing of EHR adoption could be an important factor in externalities of EHR, and this is an interesting future research question.

Endogeneity is a key empirical challenge when studying the economic effects of IT adoption, including EHR. We were able to address major potential issues. If more complex patients select into hospitals that have higher EHR use, this would result in a finding consistent with our results. To address this issue, we tested the relationship between EHR adoption and patient complexity of the adopting hospital and the neighboring hospitals, and we did not find significant correlations. We also addressed reverse causality by using the timing of changes in EHR adoption and healthcare costs, and we find evidence supporting causal direction from EHR to cost spillovers. While we are pretty confident about our findings with all of the other tests and robustness checks that we conducted, there could still be other alternative explanations that we have not thought of, and this will be a limitation as in most empirical studies.

5.5. Concluding Remark

The high cost of healthcare provisions continues to be one of the major policy concerns in the United States, and EHR is expected to alleviate this problem. However, this presumption is not clear in empirical analysis, which has created debates on the effectives of EHR as a potential tool for cost reduction. Our study indicates that EHR adoption and its impacts on healthcare costs can be seen as a regional network phenomenon due to cross-hospital externalities, and hospital-level effects might underestimate the macro-level impacts of EHR investments. We found that EHR is costly for the adopting hospital, but it can benefit the neighboring hospitals in the same regional network, which provides empirical support to previous research arguing that hospitals can affect each other's outcomes through shared patients. Our results show that spillover effects are stronger when information sharing infrastructure (HIE and IDS) is present and when there are more shared patients. The findings provide evidence supporting the effectiveness of EHR adoption on reducing societal healthcare costs and establish that the macro- and micro-level relationship between EHR adoption and healthcare costs can be different. Policy makers should also consider the characteristics of the location and the data interoperability among the hospitals in the area to achieve the maximum level of benefits from EHR subsidies.

Endnotes

[1] We include hospitals that have less than three years of missing data on operational cost (from 1998 to 2012). For hospitals that have data missing for particular years, we use linear interpolation and last-known-value extrapolation. This operational data for the hospitals is then merged with the EHR-adoption data of the hospitals. For the five EHR technologies we use in the analysis (Table 1), we set adoption of an EHR technology equal to one if the status is defined as "Live and Operational" in the hospital, and zero otherwise. For hospitals with missing information on any of the EHR systems across all years, we made a conservative assumption that the system with missing data is not yet operational in that hospital for the entire duration of the panel, which would make it more difficult to find a significant coefficient. Accommodating hospitals with missing data allows us to maximize the regional representation of hospitals in the HSA. Therefore, we are measuring the real effects of EHR systems that are truly operational. Hospitals that had an operational cost in the top 5% or the bottom 5% of observations were dropped from the analysis to avoid effects due to outliers. Hospitals in the noncontiguous United States were also dropped from the analysis.

[2] http://www.dartmouthatlas.org/data/region/ (last accessed May 17, 2017).

[3] We use high-tech industry classifications from Bureau of Labor Statistics (2005).

[4] Our results are robust to clustering by HSA and year.

[5] Adoption of an additional EHR system in a hospital increases the variable *Focal hospital EHR* by 0.2 (there are five EHR systems and this measure is between zero and one). The coefficient of *Focal hospital EHR* in the current year is 0.091 (column (1)). Therefore, the effect of an additional EHR system adoption by the focal hospital on its costs in the current year is $0.2 * 0.091 = 0.018$, corresponding to a 1.8% increase in costs. To calculate the cumulative effect over four years, we add up coefficients of current and lagged *Focal hospital EHR* in column (4), which is 0.113 $(0.056 + 0.012 + 0.014 + 0.031)$. This cumulative effect is statistically significant at the 1% significance (s.d. = 0.017). Similarly, the effect an additional EHR system adoption by the focal hospital on its costs in four years is $0.2 * 0.0113 = 0.0226$, which corresponds to a 2.3% increase in costs. We calculate the marginal effects for the effect an additional EHR system adoption by neighboring hospitals (*Other hospital EHR*) in a similar manner.

[6] Ideally, we would like to identify which HIE the hospitals belong to; however, the HIE names are not standardized across hospitals or over years in the HIMSS database. The same HIE can be represented with many different names or abbreviations for different hospitals or for different years. Therefore, we use whether the hospital is part of any HIE.

[7] An HSA is defined as urban if the majority of the ZIP codes in the HSA are classified as urban ZIP codes based on the U.S. Census.

[8] We used a dummy variable based on the median average distance because the distribution of average distances across HSAs is highly skewed, which makes the interpretation of the average distance coefficient (an increase in average distance by one mile) empirically less feasible compared to classifying areas that are above and below the median distance.

[9] Results of all of these additional robustness tests are available on request.

[10] Back-of-the-envelope calculations using our estimates indicate that if one hospital in each HSA adopts an additional EHR system, it would correspond to $5 billion in total EHR expenditures and $23 billion reduction in overall healthcare costs, leading to a net cost reduction of around $18 billion. We calculate the aggregate effect of increase in one more EHR system adoption for one hospital in each HSA that has more than one hospital, which corresponds to 483 hospitals out of 1,614 hospitals (30% of the hospitals) increasing their EHR adoption level by 0.2 in our sample (since EHR adoption is between zero and one for five systems, one more system adoption would increase this variable by 0.2). If 30% of the hospitals increase their EHR adoption by 0.2, overall EHR adoption will increase by 0.06 $(0.3 * 0.2)$. This increase is empirically reasonable, as we observe similar rates of change in the data; however, in this calculation, we assume that this change is distrusted among all of the HSAs that have more than one hospital. Then we calculate the implementation costs of this change for hospitals (according to their average bed size) in our sample by using average estimated cost of EHR adoption as $14,500 per bed and annual maintenance cost of $2,700 per bed (Congressional Budget Office 2008). It should be noted that these cost figures based on a Congressional Budget Office 2008 report might be outdated by now; however, we are not aware of more current nationally representative statistics that can be applied to our sample that are at the national level.

[11] In the fee-for-service model, doctors and hospitals are paid based on the number of healthcare services they deliver, such as tests and procedures. The value-based payment model, which is becoming more prevalent across the nation, focuses on quality rather than volume, and providers are paid based on better health outcomes.

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