THE UNINTENDED CONSEQUENCES OF THE ADOPTION OF ELECTRONIC MEDICAL RECORD SYSTEMS ON HEALTHCARE COSTS

A Dissertation
Submitted to
the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree
DOCTOR OF PHILOSOPHY

---

by
Kartik K. Ganju
May 2016

Examining Committee Members:

Paul A. Pavlou, Thesis Advisor, Department of MIS
Hilal Atasoy, Department of Accounting
Brad Greenwood, Department of MIS
Ritu Agarwal, DOIT Department, University of Maryland
Nathan Fong, External Member, Department of Marketing

ABSTRACT

In my dissertation, I study unintended consequences of the adoption of EMR systems. In my three essays, I examine how the adoption of EMR systems affects neighboring hospitals (spillover effects), can be used by hospitals to further its objectives in an unconventional manner ("upcoding" of patient case mix data), and how EMR adoption may end in the eventual abandonment of the system along with corresponding negative effects. In my first essay, I examine if the adoption of EMR systems has effects beyond the adopting hospital to neighboring hospitals. I find that the adoption of these systems has "spillover" effects to neighboring hospitals and that although the adoption of EMR systems leads to an increase in the operating cost of the adopting hospital, spillover effects reduce the operational cost of neighboring hospitals. In the second essay of my dissertation, I examine if an unintended consequence of the adoption of EMR systems is that there could be an increase in "upcoding" activities by hospitals. Upcoding deals with patients being diagnosed in such a manner as to increase the reimbursement of hospitals by inappropriately increasing the patient's case mix. Using the roll-out of an auditing program as a natural experiment, I find that there is evidence to suggest upcoding by hospitals, particularly by for-profit hospitals. Finally, in the third essay of my dissertation, I examine the phenomenon of abandonment of EMR systems and find that the abandonment of EMR system leads to an increase in the operational cost of hospitals. Having identified that abandoning EMR systems is detrimental to the operation of hospitals, I examine which hospitals are more likely to abandon their EMR systems and find that smaller hospitals are more likely to abandon these systems. I argue that the adoption of EMR systems often has unanticipated and unintended consequences.

ACKNOWLEDGMENTS

I would like to thank a number of people who were instrumental in the successful completion of this dissertation. First, I would like to thank Dr. Paul Pavlou who has been advised my though the course of doing this dissertation for his patience, advice and support. I would also like to think Dr. Hilal Atasoy with whom I have worked closely and for her time while I have explored various ideas. Similarly, Dr. Pei-Yu Chen has been invaluable for the advice she provided early on in my time as a PhD student. Dr Brad Greenwood, Dr. Ritu Agarwal and Dr. Nathan Fong have also provided valuable advice at various points and I hope to continue to build on this advice as I take this work forward.

I would also like to thank other faculty here at Fox including Dr. Munir Mandviwalla who has provided support both at the departmental level as well as my Graduate Advisor. Other faculty such as Dr. Sunil Wattal, Dr. Youngjin Yoo, Dr. David Schuff have all provided help in research as well as teaching. Additonally, I would like to thank the PhD students at Fox with whom I have developed friendships during my time here while we have discussed numerous topics.

Lastly, I would like to thank my parents Ashok and Deepika, brother Jayant and Tanya without whom this would not have been possible. Thank you.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 : INTRODUCTION AND OVERVIEW

1.1 Introduction

In 2012, health expenditure in the US stood at $2.8 trillion, and this figure is estimated to grow to $5.1 trillion by 2023, outpacing the expected growth rate of GDP in the corresponding period (CBO 2008; Centers for Medicare & Medicaid Services 2010). On a per-capita basis, US healthcare spending is three times more than other high-income OECD countries. Considering their alarming level and anticipated growth, policy makers in the US have been trying to find methods to reduce costs of providing health services.

One of the ways that policy makers have been hoping to reduce the cost or provision of health services is by the adoption of Health Information Technology (HIT) in hospitals. To encourage the adoption of HIT, the US Congress passed the Health Information Technology for Economic and Clinical Health (HITECH) Act, which provides incentives for hospitals to adopt Electronic Medical Record (EMR) systems while it penalizes hospitals that are unable to demonstrate that they are using these systems in a meaningful manner. The stated goals of the Act were that the adoption of HIT and its use would "reduce[s] health care cost[s] resulting from inefficiency, medical errors, inappropriate care, duplicative care and incomplete information" (2009). This has forced hospitals to adopt EMR systems bringing about significant changes in the provision of healthcare across the US.

This had led researchers to study the impacts of the adoption of these systems. Researchers have examined the impacts that these systems are having on financial and clinical metrics of hospital and have found both positive and negative impacts of the adoption of these systems (Chaudhry et al. 2006; Sidorov 2006).

However, scholars have pointed out that purposeful action (in this case the adoption of EMR systems) often has unanticipated outcomes (Merton 1936). These unanticipated outcomes have been reasoned to be both positive and negative in nature and occur due to a limit in understanding of the outcomes that actions may have before these actions were undertaken. While there is a large literature that has examined the effect of these systems in hospitals across the US, I propose studying three unanticipated ways (outlined in the following section) in which the adoption of EMR systems may be affecting the cost of providing healthcare services. While it was hoped that the adoption of EMR system would reduce the cost of the provision of healthcare (by reducing the number of tests and care as envisaged in the HITECH act), I find that the effect may not be straightforward. Instead, the impact of the adoption of these systems is dependent on unanticipated ways that the systems may be used.

1.2 Dissertation Overview

In the essays that comprise my dissertation, I seek to examine three mechanisms by which the adoption of EMR systems may be affecting healthcare costs in unanticipated ways. In the first essay, I examine the effect of the adoption of EMR systems by a hospital on neighboring hospitals. I argue that while the HITECH act envisaged that the adoption of EMR systems would lead to a reduction in the care provided in the adopting hospital, due to patient mobility from one hospital to the neighboring hospitals, there could be spillover effects. Patients may take better care (and records) that are provided in the hospital that adopts EMR systems leading to cost reductions in neighboring hospitals.

In the second essay of my dissertation, I examine if EMR systems are being used by hospitals strategically to increase their reimbursements from Medicare. I argue that the increased automation that EMR systems can enable hospitals to insert data into the chart of the patient that is in excess of the level of care that is provided. While it was hoped that the adoption of EMR systems would reduce the cost of provision of healthcare, my results indicate that the adoption of EMR systems is allowing hospitals to bill Medicare an additional $300 million per annum. However, steps taken by Medicare to provide oversight can mitigate the ability of hospitals to request additional reimbursements.

In the third essay of my dissertation, I study the abandonment of EMR systems on healthcare costs. I examine the different types of abandonment of systems that hospitals may undertake and examine the effect of hospital characteristics and the presence of the HITECH Act on abandonment characteristics for the US.

Together, in these three essays I highlight how the adoption of EMR systems may not always have an impact in the ways that were anticipated. These unanticipated effects can be both positive and negative and can lead to both increases and decreases in the cost of operation of hospitals. Overall, it is important for policy makers to be aware of the ways in which EMR systems end up being used. This can then be used to continuously update policy to take into account the use of these systems in ways that were not initially envisaged.

In the next three chapters, I outline research that I have undertaken on the effect of the adoption of EMR systems on costs in hospitals. I propose building on this research towards a richer understanding of the effect of the adoption of EMR systems. In chapter 5, I summarize the findings that I have to date.

CHAPTER 2 : THE SPILLOVER EFFECTS OF HEALTH IT INVESTMENTS ON REGIONAL HEALTH CARE COSTS

Electronic health records (EHR) are often presumed to reduce the significant and accelerating health care costs in the US. However, evidence on the relationship between EHR adoption and costs is mixed, leading to skepticism about the effectiveness of EHR. We argue that the benefits of EHR systems can go beyond the adopting hospital as they create regional spillovers via patient and information sharing among hospitals. When patients switch between providers, high quality care and 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. These effects are stronger for the hospitals that are in the health information exchange networks and in the same integrated delivery systems. We find that the urban areas with denser hospital locations experience higher regional spillovers suggesting that the spillovers are driven by shared patients. Our estimates suggest that around $5 billion in EHR investments can lead to a net reduction of about $18 billion in national health care costs via regional spillovers. This finding suggests that we need to take into account such regional spillover to understand the real benefits of health IT investments and form policy decisions.

2.1 Introduction

The cost of health care continues to be the subject of several policy debates in the US. In 2012, health expenditure was $2.8 trillion, and this figure is estimated to grow to $5.1 trillion by 2023, outpacing the expected growth rate in GDP in the corresponding period (CBO 2008; Centers for Medicare & Medicaid Services 2010). The US health care system is criticized as being fragmented and uncoordinated leading to large number of preventable medical errors and wasteful resource allocation (McCullough et al. 2013). These problems have been estimated to cause an operational waste between $126 billion and $315 billion in the US health care industry (PwC Health Research Institute Report 2010). 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 2009 Health Information Technology for Economic and Clinical Health Act (HITECH Act), part of the American Recovery and Reinvestment Act, which allocates around $19 billion to increase EHR adoption by health care 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 health care costs and improve the quality of care. EHR is expected to improve communication and information exchange, leading to better diagnostics and quality of care, which in turn can translate into lower costs with a reduction in medical errors, unnecessary re-admissions, over-testing, and 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 health care *costs* is more scarce and mixed (Jones et. al. 2012). The conflicting findings question the role of EHR in health care providers' productivity and the effectiveness of EHR as a policy tool that facilitate 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 (Lichtenberg 1995, Brynjolfsson and Hitt 1996, Brynjolfsson and Hitt 2003). The IT productivity literature shows that organizations achieve gains from IT investments as they make several complementary changes in their business processes (Bresnahan and Greenstein 1996, Brynjolfsson et al. 2002, Brynjolfsson and Hitt 2003, Dedrick et al. 2003). Studies also 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 (Cheng and Nault 2007; 2012, Han et al. 2011, Chang and

Gurbaxani 2012, Bloom et al. 2013, 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, Lee et al. 2011, Landon et al. 2012). A significant portion of patients in a hospital is 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 directly via referrals and indirectly (Landon et al. 2012, Barnett et al. 2011, Barnett et al. 2012).

Combining the IT spillover and hospital network literatures, we argue that inter-hospital patient and information sharing can create a link between the EHR adoption of one hospital and the costs of another hospital. When a patient transfers from one hospital to another, *better records and information availability* about the patient can facilitate coordination of care with improved knowledge about the diagnosis, complications, and procedures. The improved knowledge and care coordination can improve care quality and prevent redundancy and thus reduce costs for the second hospital (Ayabakan et. al 2015, Lammers et al 2014). This mechanism suggests that are potential spillover effects in a network of hospitals. However, most empirical studies on EHR focus on hospital level effects, and we are not aware of any study that empirically quantifies the spillover effects.

Our goal in this research is to investigate the regional spillover effects of EHR adoption by a hospital on the costs of neighboring hospitals in the same Health Service Area (HSA). We use data from several sources that link EHR adoption to the costs and other characteristics of hospitals between 1998 and 2012. Hospital fixed effects model is used for the main specifications, and we address the endogeneity issues with several tests. Our findings indicate that while EHR adoption increases operational costs for the adopting hospital, it significantly decreases the total costs of the other hospitals in the same HSA. The results indicate that adoption of one more EHR system in a hospital leads to a 1.8 percent increase in its own costs in the current year and a cumulative effect of 2.3 percent increase in costs over four years. A similar adoption of one more EHR system in the focal hospital corresponds to 1 percent decrease in the total costs of the other hospitals in the same HSA in the initial year, and a cumulative effect of 1.5 percent decrease in four years. We found that both basic and advanced EHR create significant spillover effects. The spillover effects are stronger if more hospitals in the region are in Health Information Exchange (HIE) networks and Integrated Delivery Systems (IDS) that increase the likelihood of information sharing. Additionally, urban locations and areas where hospitals are more densely located realize higher regional spillover. We also examined the regional distribution of EHR systems in the network, and found that regional cost reductions are stronger when advanced EHRs are concentrated in some hospitals in the HSA. The findings provide evidence for cross-hospital externality and show that EHR adoption, while costly for the adopting hospitals as they incur high expenditures, can lead to cost reduction for other hospitals in the area.

We make several contributions to the literature on the relationship between EHR adoption and health care costs, and provide important public policy implications. First, 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 the effectiveness of EHR as a potential solution to reduce overall health care costs and understand its macroeconomic impact. The distributional characteristics of EHR systems among the hospitals in the regional network are found to be an important determinant of how the benefits of EHR on healthcare costs are realized. In the long run, society would benefit from all hospital adopting all EHR systems to achieve higher quality and coordination of care. However, our findings suggest that, instead of enforcing a strict policy that all hospitals adopt EHR in a short period of time, which can be very expensive not only for the government but also for many hospitals initially, a more cost effective strategy could be to focus on EHR investments in a subset of hospitals as a priority and the interoperability among the hospitals.

2.2 Literature Review and Theoretical Development

2.2.1 The effects EMR adoption on adopting hospitals' costs

There can be at least two forces through which EHR adoption impacts the 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 to $1.35 million (CBO 2008). On the other hand, these technologies can introduce several improvements that can in turn lead to reduced costs. EHR applications are usually found to increase health care quality by enabling better 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 (Buntin et al. 2011, Chaudhry et al. 2006, Athey and Stern 2000, Borzekowski 2009, (McCullough et al. 2013). These improvements in health care quality can decrease the waste that is prominent in US health care 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 diagnostics and patient care can further decrease the costs by preventing medical errors, unnecessary re-admissions and ER visits.

The empirical evidence on the relationship between EHR adoption and health care 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 percent of the US hospitals adopt EHR, potential savings could add up to $80 billion over fifteen years. These efficiency savings are estimated to arise from avoiding adverse drug events, improving disease prevention, managing 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 1987-1994. 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 2013). Dranove et al. (2014) found an increase in hospital costs with EHR adoption, on average. The 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 still debatable whether and how EHR adoption compensates the large initial implementation costs for hospitals. Therefore, it is unclear whether hospitals can absorb the hefty adoption costs of EHR in order to reap the benefits of improved quality of care of the patients, thus creating a potential incentive issue for hospitals to further invest in EHR.

2.2.2 The spillovers effects of EMR adoption on regional health care costs

Previous studies have focused on the hospital level effects of EHR adoption, which are certainly important. However, the impacts of EHR adoption can go beyond the adopting hospital, as regional spillover effects of EHR adoption can arise from network externalities. To establish the spillover effects of EHR adoption, we discuss 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 and barcodes are subject to such externalities (e.g. Katz et al. 1985; Markus et al. 2006; Zhu et al. 2006). IS research document that firms can benefit from IT investments of other firms through mechanisms such as labor mobility, inter-industry transactions, and trading (Cheng and Nault 2007; 2012, Han et al. 2011, Chang and Gurbaxani 2012, Bloom et al. 2013, Tambe and Hitt 2014). Cheng and Nault (2007) found that gains from IT 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 spillover to suppliers with enhanced exchange of more accurate information (Cheng and Nault 2012). Thus, the benefits of IT can spillover 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 from other firms from which they hire labor (Tambe and Hitt 2014). Studies also show that the IT contributions to gross output are greater than private IT returns, which implies that IT investments have externalities that are economically significant and contribute to long-term productivity (Brynjolfsson and Hitt 1995, Anderson et al. 2003, Chang and Gurbaxani 2012).

In the context of health care, we expect that network externalities arise from patient sharing among hospitals, which are consistent with both *coordination and efficiency spillovers* arguments in the IT productivity literature. Hospitals that are geographically co-located are considered to be a network (Lee et al. 2011). They are often connected to each other through shared patients, because patients are treated at or admitted to different hospitals in the same region, especially over time (Huang et al. 2010; Lee et al. 2011; McCullough et al. 2013). Patient sharing usually happens through two channels: direct sharing, when a patient is referred from one hospital to another, or indirect sharing, when a patient is admitted to another hospital without referral from the first hospital. 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 have measured the links between physicians by the number of shared patients and have documented that physicians at different hospitals share patients and information about the patients (Landon et al. 2012, Barnett et al. 2011, Barnett 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, either directly by a referral or indirectly for other reasons, this transfer might reflect in the costs of Hospital B. *Availability of information and records* about a patient's history, diagnosis, procedures, and complications due to EHRs can facilitate improved *patient care coordination* and quality of care at the 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 re-admissions, and reductions in duplicate testing within and across settings. EHR systems usually enable coordination but EHRs by themselves do not guarantee to a seamless electronic exchange of information between hospitals. For a direct information transfer between hospitals to occur, hospitals need to be part of Health Information Exchange (HIE). This information exchange then can improve patient care coordination. For example, Lammers et al. (2014) found that patient information sharing across hospitals leads to lower repeated imaging. Patients were 59 percent less likely to have a redundant CT scan, 44 percent less likely to get a duplicate ultrasound, and 67 percent 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. (2015) find inter-hospital information sharing is associated with lower levels of duplicate radiology imaging when patients switch between hospitals. Major improvements in communication and care coordination are expected via HIEs, but better record keeping with EHR could potentially enable availability of patient information to neighboring hospitals even in the absence of HIE. Printing and faxing discharge summaries and direct information exchange between physicians involved in referrals can still facilitate information exchange between two providers (Kripalani et al. 2007) albeit at a lower rate.

Overall, while empirical studies on EHR adoption have focused on hospital level effects, we expect patient and information sharing to create significant EHR spillover effects among hospitals in a region. Thus, it can be important to take a regional or network perspective to study the impact of EHR adoption on health care costs. The goal of this paper is to quantify such spillover effects from EHR adoption on health care costs of neighboring hospitals.

2.3 Data

We obtained hospital level EHR adoption information 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 (Miller and Tucker 2011, Dranove et al. 2014, Parente and McCullough 2009, McCullough et al. 2013). We use operational cost data of hospitals from the Medicare Cost Reports database. We obtain other hospital level characteristics such as number of beds, number of discharges, and number of employees from Medicare data. We merge HIMSS data with Medicare data to construct a hospital level panel between 1998-2012.[1]

To measure the spillover effects, we consider hospitals that are in the same Health Service Area (HSA) as a network. HSAs are the nationally legislated local health care markets for hospital care that are created for health planning purposes. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area. A health service area can be a county, a large metropolitan city, a state, or some other geographical unit that meets the HSA criteria[2]. HSA information is publically available through State and Federal regulatory and health planning agencies. We choose HSA as a network because it is the most granular, well-defined health care market, which is also 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, our estimates can present a lower bound estimate of spillover effects compared to a case where patients are mobile beyond HSA, and we can expect the overall spillover effects to be stronger when measurement is not limited to a 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 of one hospital to

---

[1] We include hospitals that have less than 3 years missing data (from 1998-2012). For hospitals that have data missing for particular years, we use linear interpolation and last known value extrapolation. This leaves us with 4278 hospitals for which we have data for 15 years. This operational data for the hospitals is then merged with the IT 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 1 if the status is defined as "Live and Operational" in the hospital, and 0 otherwise. For those hospitals with missing information on any of the EHR systems in a particular year, we made a conservative assumption that the system with missing data is not yet operational in that year. Therefore, we are measuring the real effects of ERP systems that are truly operational. Hospitals that had an operational cost in the top 5% or the bottom 5% of observations were dropped from analysis to avoid effects due to outliers. Hospitals in the non-contiguous US were also dropped from the analysis.

[2] HSAs are defined in the National Planning and Health Resource Act of 1974. The criteria for determining a HSA can be found in the beginning of Part B of the act: https://www.adph.org/ALPHTN/assets/history_law.pdf

the costs of other hospitals, we drop HSAs in which there is only one hospital, as spillovers across hospitals cannot be calculated. This leads to 1614 hospitals in 483 HSAs in our panel (1998-2012), and an average of around 3.3 hospitals per HSA.

We used American Community Survey data of the US Census at the Zip code level to calculate the HSA level demographic control variables such as population, age, 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 added basic demographic characteristics of the HSA that might affect the health care costs such as age, income, and education. We also used other county, state, and regional 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). We utilized a similar measure as Dranove et al. (2014) and calculated the ratio of high-tech establishments to the total number of establishments in the county using US Census County Business Patterns data and high-tech industry classifications from Bureau of Labor Statistics[3]. At the state level, we used the average nurse salaries to control for the labor costs that hospitals face as nurse salaries is a major component of labor costs for hospitals.

2.3.1 Measuring EHR adoption

There are five major EHR applications 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 observed the adoption of these systems for each hospital-year observation.

---

[3] The BLS high-tech sector categorizations are used: http://www.bls.gov/opub/mlr/2005/07/art6full.pdf

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 a hospital. A Clinical Decision Support System (CDSS) helps medical providers in diagnosing patients. Further, this technology can help in outlining treatment plans for patients and checking for drug interactions. Order Entry (OE) allows hospitals to streamline hospital operations by replacing paper forms and allowing the electronic transfer of documents. Advanced EHR technologies are the Computerized Physician Order Entry (CPOE) or the adoption of Physician Documentation (PD). CPOE systems enable physicians to enter medical orders that are integrated with other patient information and can be can be 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 descriptions and adoption rates for each technology for the initial and final year of our sample, 1998 and 2012 respectively.

The HIMSS database provides information about the adoption of EHR systems. A specific EHR system was considered to be "adopted", if the hospital reported that the system's status was "live and operational" in a given year. However, we cannot measure the extent and degree of use with measure. For example, we can tell that a hospital adopted a CPOE system but it is difficult to identify how many units in the hospital use the CPOE and for which applications. This is an inevitable limitation of the HIMSS data. The potential value of spillover effects is likely to be realized during the post-adoptive "use" phase. However, this limitation does not create a problem for our findings as we expect our results to be stronger if we could measure "use" instead of "adoption". Let's suppose only a percentage of hospitals are in active use after adoption and our findings most likely are driven by these hospitals. If we can still find a significant average effect for all the hospitals that have adopted EHR, the average effect would be larger if we could identify the ones that are active EHR usage. Adoption is not a measure of usage, but it is a prerequisite and signal of usage, and they move in the same direction. Therefore, our results can be interpreted as the lower bound spillover effects, and inability to observe 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 applications (5 applications) as a measure of EHR adoption level. We should emphasize that this measure goes beyond simple adoption of EHR and reflects the number of EHR applications that are actually operational in the hospital. This variable changes between 0 and 1, 1 indicating all the EHR applications are adopted. We further distinguished basic EHR applications and advanced EHR applications. For example, HIMSS (2011) groups Clinical Data Repository, Clinical Decision Support System and Order Entry into basic EHR category, and Computerized Physician Order Entry and Physician Documentation into Advanced EHR category. We also calculate the dispersion of EHR adoption in the HSA with a Gini coefficient to test whether spillovers are stronger in areas where EHR adoption is more unequal (please see section 4.3 for details on the calculation of the Gini coefficient).

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 the patient	31%	66%
Clinical Decision Support System (CDSS)	Help medical practitioners with diagnosis and treatment plans	30%	63%
Order Entry (OE)	Allow hospitals to replace paper forms with electronic documents	33%	65%
Computerized Physician Order Entry (CPOE)	Allow providers to enter medication, laboratory and radiology orders which are directly incorporated with patient information	5%	40%
Physician Documentation (PD)	Allow physicians to maintain electronic records about patients' conditions. System can also inform doctors about conditions they may have overlooked.	8%	35%

2.3.2 Operational Costs

We use hospital level operational costs, which is a common dependent variable in the literature on EHR impacts on health care costs. We obtain this information from Medicare cost reports. The operational costs have seven components. Table 2 describes the different cost components and their average share in total operational costs in our sample. Additionally, each cost category can be broken down into salary and non-salary components. We see that general services costs, ancillary services costs and inpatient costs constitute the majority of total operational costs. We differentiate the impacts of EHR on each cost category as well as salary vs. non-salary components as a robustness check.

Table 2: 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	Costs related to the 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	Costs for clinic or emergency centers related to outpatients	6%
Non-reimbursable	Cost centers including research and gift, flower, coffee shop	4%
Other reimbursable	Cost for home program dialysis and other durable medical equipment	2%
Special purpose	Cost for lung, kidney, liver and cost of other organ acquisition (including ambulatory surgical center)	2%

2.3.3 Summary Statistics

Table 3 presents the summary statistics for the main dependent variables, independent variables, and control variables used in the analysis. The mean EHR adoption level is 0.38, meaning on average hospitals have 38% of all the EHR systems. The average operational cost for a hospital in our sample is $1.24 million. In terms of size, the average number of beds in a hospital in our sample is 150.

Table 3: Descriptive Statistics

VARIABLES	Mean	Std. Dev.	Observations
EHR (between 0 and 1)	0.38	0.33	24210
Basic EHR (between 0 and 1)	0.52	0.42	24210

Advanced EHR (between 0 and 1)	0.23	0.42	24210
Gini EHR (between 0 and 1)	0.33	0.20	24210
Gini Basic EHR (between 0 and 1)	0.44	0.26	24210
Gini Advanced EHR (between 0 and 1)	0.22	0.26	24210
Operational Cost (in million $)	1.24	1.08	24210
Hospital Level Controls			
Number of Discharges	7022	6613	24210
Total Bed Admittance Days	34619	28517	24210
CMI	1.43	0.27	16545
Outpatient Charges (in million $)	1.08	1.35	23730
HSA Level Controls			
Percent 65 years and older, percent	13.01	3.55	24210
Percent college graduate	28.83	10.63	24210
Total Population (in million)	1.07	1.30	24210
Log Median Household Income	53321	13566	24210
Other Regional Level Controls			
Ratio of IT firms in county	0.03	0.01	24210
Average Nurse Salaries in State	65290	8793	24210

2.4 Empirical Specification and Results

2.4.1 Empirical Specification

Our main goal is to estimate the degree of spillover effects by which EHR adoption by a hospital affects the costs of other hospitals' in the same region. We measure the regional spillover effects at the HSA level by calculating the total costs of all hospitals in the HSA except the focal hospital. Hospital operational costs are deflated and adjusted for price inflation. We use yearly EHR adoption as the key independent variable, measured by the level of EMR adoption (between 0 and 1).

We investigate how changes in EMR adoption by a hospital affect its own costs as well as the costs of other hospitals in the same HSA. We estimate the following fixed-effect models for our main analysis:

$$\text{Log (Cost)}_{i,t} = \beta_0 + \beta_1 \text{EHR}_{it} + \beta_2 \text{EHR}_{it-1} + \beta_3 \text{EHR}_{h-i,t} + \beta_4 \text{EHR}_{h-i,t-1} + \theta X_{it} + \delta Z_{ht} + \phi G_{h-i,t} + \alpha_i + \lambda_t + e_{it} \qquad \text{[eq. 1]}$$

where the dependent variable Log $(\mathrm{Cost})_{i,t}$, is the deflated operating cost of hospital i at time t. The first main independent variables of interest, EHR_{it}, is the level of operational EHR at hospital i at time t. Again, we want to emphasize that this variable does not measure the effect when EHR is first acquired but estimates the effect of EHR applications that are truly operational. That is, we measured the effects from real adoption and usage of EHR, since simple acquisition without being operational should not affect other hospitals. Therefore, β_1 measures the effect of EHR adoption of the focal hospital on the costs of focal hospital. To capture potential lagged effects from EHR adoption, we also added EHR_{it-1}, which is the EHR adoption level at hospital i at time t-1, and β_2 measures the lagged effect of EHR adoption of the focal hospital. We added more lagged variables 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 second independent variable of interest is $\mathrm{EHR}_{h-i,t}$, 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. Additionally, we controlled for several hospital and regional characteristics that might influence the impact of EHR adoption on hospital's own cost and on the regional spillovers on other hospitals' costs. X_{it} includes time-variant hospital level characteristics such as number of beds, number of employees, number of discharges and number of bed admittance days. We added case mix index and outpatient charges to control for the level of severity of cases in the hospital in further specifications (Section 4.4). Z_{ht} represents HSA level control demographics such as population, population density, race, age, and education. We have these HSA level demographic characteristics for one year and we multiply these values by the time trend following Dravone et al. (2014). We further controlled 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 cost in the region. Additionally, hospital fixed effects (α_i) control for time invariant heterogeneity across different hospital characteristics. Year fixed effects (λ_t) enable us to control for nation-wide shocks to the economy and health care system that are experienced by all health care providers. Additionally, we controlled for other time variant characteristics of these other hospitals in equation. $G_{h-i,t}$ 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. In all specifications, standard errors are clustered by hospital and year. However, these characteristics of the neighboring hospitals do not affect the costs of the focal hospital and do not change the effects of the EHR adoption of the focal hospital and the spillover effects. Finally, e_{it} is the random error, which captures unobserved random factors that may have had an effect on health care costs.

2.4.2 Endogeneity and Identification Strategy

The relationship between EHR adoption and regional cost spillovers has potential endogeneity issues. First, there can be patient selection; patients with different diseases and complexities can select into hospitals based on hospitals' EHR investments. Presence of EHR technologies can be advertised by hospitals, and 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. Similarly, this can lead to surrounding hospitals to be left with less severe and less complicated cases that are easier to treat, and require lower operational costs. Therefore, EHR investments can potentially change the patient pool for the EHR adopting hospital and also for the surrounding hospitals. This scenario offers 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 that control for the complexity of patients. Second, we directly test whether CMI and outpatient charges change after

EHR adoption and find that EHR adoption does not significantly change the patient profile of hospitals.

Second, reverse causality might occur if reductions in EMR adoption of neighboring hospitals follow the EHR adoption of the focal hospital. We exploit the panel structure of our data and test the relationship between timing of changes in EHR adoption and costs to address potential reverse causality. We find that lagged EHR adoption of the neighboring hospitals is significantly correlated with the current costs of the focal hospital. We also find that the lead of EHR adoption is not significantly related to the current costs, and this relationship would be significant if changes in costs lead to changes in EHR adoption. These findings combined together provide evidence that changes in costs follow changes in EHR adoption and not the other way around, supporting a causal direction from EHR adoption of the neighboring hospitals to the costs of the focal hospital.

Third, there can be confounding factors or a spurious correlation between EHR adoption of neighboring hospitals and costs of focal hospital. We used hospital fixed effects that controlled for the unobserved time-invariant heterogeneity among hospitals. However, there still may have been a time-varying confounding factor that affected both EHR adoption and costs of hospitals and that was not related to spillovers, and this could have led to a spurious correlation between these variables. We conducted a falsification test to address this issue. Since the spillover mechanisms rely on the connections between the hospitals such as shared patients and information, we do not expect externalities to materialize for hospitals that are located too far from each other for such a connection to occur. If significant effects were found between very distant hospitals that were not co-located, it would indicate a potential problem. We do not find any significant spillover effects for hospitals that are very distant from each other (East coast vs West of the US).

2.4.3 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 especially in the current year when an EHR application is first brought alive and can impact the costs in the subsequent years, consistent with other studies that have used HIMSS data (Dranove et al. 2014).

Interestingly, the coefficients of other hospital's EHR adoption in the HSA excluding the focal hospital are negative and significant over time. These indicate significant spillover effects from EHR adoption of neighboring hospitals on the focal hospital's costs. There is evidence supporting that although the cost increases at the hospital that is making the EHR investment, it can lead to reduction in the costs of providing care for co-located hospitals. The results indicate that adoption of one more EHR system in a hospital leads to a xx% increase in its own costs in the current year and a cumulative effect of x% increase in costs over xx years. A similar adoption of one more EHR system by the neighboring hospital in the HSA corresponded to a xx% percent decrease in the total costs of the focal hospital in the initial year, and a cumulative effect of xx% decrease in xx years.

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***	-0.028**	-0.029**	-0.026**
	(0.010)	(0.012)	(0.012)	(0.012)
Other Hospitals EHR (t-1)		-0.025*	0.001	0.000
		(0.013)	(0.014)	(0.014)
Other Hospitals EHR (t-2)			-0.041***	-0.016
			(0.013)	(0.015)
Other Hospitals EHR (t-3)				-0.034***
				(0.013)
Focal Hospital EHR	0.091***	0.061***	0.059***	0.056***
	(0.007)	(0.008)	(0.008)	(0.008)
Focal Hospital EHR (t-1)		0.041***	0.014	0.012
		(0.009)	(0.009)	(0.009)
Focal Hospital EHR (t-2)			0.037***	0.014
			(0.008)	(0.009)
Focal Hospital EHR (t-3)				0.031***
				(0.009)
Hospital Level Controls				
Log Number of Discharges	0.151***	0.154***	0.156***	0.161***
	(0.017)	(0.018)	(0.019)	(0.020)
Log Bed Admittance Days	0.015*	0.010	0.007	0.004
	(0.008)	(0.008)	(0.008)	(0.008)

HSA Level Controls				
Percent 65 years and older * Year	0.042	0.103	0.070	-0.025
	(0.133)	(0.146)	(0.156)	(0.171)
Percent college graduate * Year	-0.046	-0.028	-0.011	0.015
	(0.047)	(0.050)	(0.054)	(0.060)
Log Total Population * year	-1.295***	-1.178***	-0.975***	-0.948**
	(0.321)	(0.341)	(0.368)	(0.402)
Log Median Household Income * Year	2.678	1.258	0.469	-0.757
	(1.896)	(2.018)	(2.155)	(2.414)
Other Regional Level Controls				
Ratio of IT firms in the county	1.657***	1.759***	1.053	1.310*
	(0.595)	(0.639)	(0.682)	(0.784)
Log Average Nurse Salaries in State	0.325***	0.322***	0.299***	0.299***
	(0.059)	(0.063)	(0.063)	(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

Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

We analyze the spillovers effects of EHR adoption on different types of cost categories. If information sharing leads to decrease in redundant tests, imaging and other lab work, we expect this effect to be prominent the general cost category (which includes equipment costs) as well as ancillary cost category (which includes laboratory, tests and associated costs). Additionally, other cost categories such as inpatient and outpatient services can be affected if there are other externalities due to improved coordination of care. In Table 5, we decompose the total costs into seven components (1a-7a), where each coefficient is coming from a separate regression. The first four cost categories constitute 86% of the total costs. We find that there are significant spillovers on all major cost components including the general services, ancillary services (tests, labs etc.), and inpatient and outpatient services (Table 5). Each of the seven cost categories has salary and non-salary components. We add all the salary and non-salary parts of the seven cost categories to calculate the total salary component and non-salary component of the operational costs (1b-2b). EHR adoption has significant spillovers to both salary and non-salary components of operational costs, indicating there can be externalities both on labor costs and capital/services costs.

Table 5: Spillover Effects by Cost Categories

	(1a)	(2a)	(3a)	(4a)
DV	General	Ancillary	Inpatient	Outpatient
Other Hospitals EHR	-0.041***	-0.048***	-0.038***	-0.207***
	(0.012)	(0.015)	(0.011)	(0.032)
	(5a)	(6a)	(7a)	
	Non-reimbursable	Other reimbursable	Special purpose	
Other Hospitals EHR	-0.030	-0.036	-0.209***	
	(0.075)	(0.052)	(0.072)	
	(1b)	(2b)		
	Salary Component	Non-salary Component		
Other Hospitals EHR	-0.048***	-0.052***		
	(0.009)	(0.011)		
Hospital Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	24,210	24,210	24,210	24,210

We further differentiate between basic EHR and advanced EHR applications to test whether the spillovers are driven by a certain type of EHR. Basic EHR systems allow hospitals to replace paper forms and records with electronic copies. Technologies that enable different departments in the hospital to connect and exchange information with each other, physicians to code patient observation charts, and computer assisted diagnostics are known as advanced EHR (HIMSS 2011). We utilize this conventional distinction and analyzed regional spillover effects of basic and advanced EHR adoption on health care costs (Dranove et al. 2014). Theoretically, both basic and advanced EHR systems can create spillover effects with the proposed mechanisms of coordination and efficiency spillovers via patient and information sharing. Table 6 demonstrates the spillover effects where EHR adoption is decomposed into basic EHR adoption and advanced EHR adoption. Results indicate that spillover effects can be driven by both basic EHR and advanced EHR systems and the spillover effects of advanced ERM adoption accrue over time whereas the spillovers from basic EHR adoption are observed in the same year.

Table 6: Spillover Effects by Basic and Advanced EHR
DV: Log costs of focal hospital

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals Basic EHR	-0.022***	-0.013	-0.015*	-0.015*
	(0.008)	(0.009)	(0.009)	(0.009)

Other Hospitals Basic EHR (t-1)		-0.010	0.002	0.001
		(0.010)	(0.011)	(0.011)
Other Hospitals Basic EHR (t-2)			-0.019**	-0.010
			(0.010)	(0.012)
Other Hospitals Basic EHR (t-3)				-0.012
				(0.010)
Other Hospitals Advanced EHR	-0.029***	-0.015	-0.014	-0.011
	(0.008)	(0.010)	(0.010)	(0.010)
Other Hospitals Advanced EHR (t-1)		-0.018*	-0.001	-0.001
		(0.010)	(0.012)	(0.012)
Other Hospitals Advanced EHR (t-2)			-0.026**	-0.006
			(0.011)	(0.013)
Other Hospitals Advanced EHR (t-3)				-0.029**
				(0.012)
Focal Hospital EHR	0.091***	0.060***	0.059***	0.056***
	(0.007)	(0.008)	(0.008)	(0.008)
Focal Hospital EHR (t-1)		0.041***	0.014	0.012
		(0.009)	(0.009)	(0.009)
Focal Hospital EHR (t-2)			0.036***	0.014
			(0.008)	(0.009)
Focal Hospital EHR (t-3)				0.031***
				(0.009)
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

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.4 Results: The Mechanisms of Regional Spillovers

2.4.4.1 Health Information Exchanges

One potential mechanism for the regional spillover effects to occur is information sharing across different hospitals. Health Information Exchanges (HIE) are networks that are specifically designed for enabling information sharing among the hospitals that are part of the network. Even though the existence of HIE does not guarantee that the hospitals are sharing information seamlessly, we can assume that it would increase the likelihood of sharing of information across hospitals. Table 7 presents the results where we analyze the effects of focal hospital's and neighboring hospitals' HIE adoption on focal hospitals costs. The HIE information is available 2006 and afterwards and therefore we limit our sample to years of 2006-2012 for this analyses. We find that while focal hospital's own HIE adoption does not affect its cost significantly, the neighboring hospital's HIE adoption is negatively associated with focal hospital's costs, supporting evidence for information sharing mechanism for regional spillovers.

Table 7: Spillover Effects of HIE
DV: Log costs of focal hospital

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals HIE	-0.059***	-0.028**	-0.030**	-0.038***
	(0.013)	(0.014)	(0.014)	(0.014)
Other Hospitals HIE (t-1)		-0.079***	-0.046**	-0.028
		(0.016)	(0.019)	(0.023)
Other Hospitals HIE (t-2)			-0.066***	-0.060***
			(0.017)	(0.019)
Other Hospitals HIE (t-3)				-0.058***
				(0.018)
Focal Hospital HIE	0.011	-0.002	-0.005	0.007
	(0.007)	(0.008)	(0.008)	(0.009)
Focal Hospital HIE (t-1)		0.002	-0.019**	-0.028***
		(0.008)	(0.009)	(0.010)
Focal Hospital HIE (t-2)			0.011	0.001
			(0.009)	(0.009)
Focal Hospital HIE (t-3)				0.025**
				(0.010)
Hospital Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,031	6,811	5,623	4,443
Adj. R-squared	0.396	0.391	0.356	0.292

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, EHR adoption
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

The information sharing mechanism requires both hospitals have the HIE since that is the only way to facilitate information exchange across hospitals. In Table 8 we interact the focal hospital's HIE and neighboring hospital's HIE adoption since the information sharing mechanism requires both hospitals to be part of the same HIE.[4] We find the interaction term to be significant and negative supporting that the spillovers are stronger as focal and neighboring hospitals mutually adopt HIE.

Table 8: Spillover Effects of HIE-Interactions
DV: Log costs of focal hospital

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals HIE	-0.037***	-0.010	-0.015	-0.022*
	(0.012)	(0.013)	(0.014)	(0.013)
Other Hospitals HIE (t-1)		-0.075***	-0.050***	-0.034
		(0.015)	(0.019)	(0.025)
Other Hospitals HIE (t-2)			-0.056***	-0.056***
			(0.017)	(0.018)
Other Hospitals HIE (t-3)				-0.051***
				(0.019)
Focal Hospital HIE	0.027***	0.011	0.006	0.018*
	(0.008)	(0.008)	(0.008)	(0.009)
Focal Hospital HIE (t-1)		0.005	-0.023**	-0.033***
		(0.010)	(0.011)	(0.012)
Focal Hospital HIE (t-2)			0.020*	0.004
			(0.011)	(0.011)
Focal Hospital HIE (t-3)				0.031**
				(0.013)
Focal Hospital HIE*Other Hospitals HIE	-0.125***	-0.103***	-0.087***	-0.087**
	(0.037)	(0.038)	(0.032)	(0.035)
Focal Hospital HIE (t-1)*Other Hospitals HIE (t-1)		-0.017	0.041	0.041
		(0.044)	(0.050)	(0.050)
Focal Hospital HIE (t-2)*Other Hospitals HIE (t-2)			-0.072	-0.029
			(0.050)	(0.056)
Focal Hospital HIE (t-3)*Other Hospitals HIE (t-3)				-0.053
				(0.053)
Hospital Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,031	6,811	5,623	4,443
Adj. R-squared	0.397	0.392	0.357	0.293

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:

[4] Ideally we would like to identify which HIE the hospitals belong to, however this information is not easily available in the HIMSS database, therefore we use whether hospital is part of any HIE.

Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, EHR adoption
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.4.2 Integrated Delivery Systems

Besides the HIEs, the hospitals that are in the same Integrated Delivery System (IDS) are also more likely to share information. IDS is a network of hospitals under a parent holding company as their systems tend to be more compatible with each other. Additionally, hospitals that have are part of the same franchise might have less data blocking as the concerns for sharing among the hospitals under the same brand would be lower. We test this idea by interacting the neighboring hospitals' EHR adoption by the number of hospitals that are in the same IDS as the focal hospital (Table 9). The IDS information is available in our database 2005 onwards. We find that spillover effects of EHR adoption are stronger among the hospitals that are in the same IDS, supporting information sharing mechanism.

Table 9: Spillover Effects by Integrated Delivery System
DV: Log costs of focal hospital

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals EHR * # in IDS	-0.016	-0.021	-0.027*	-0.040**
	(0.011)	(0.014)	(0.015)	(0.017)
Other Hospitals EHR (t-1) * # in IDS (t-1)		0.004	0.005	-0.013
		(0.012)	(0.012)	(0.012)
Other Hospitals EHR (t-2) * # in IDS (t-2)			-0.007	0.003
			(0.014)	(0.014)
Other Hospitals EHR (t-3) * # in IDS (t-3)				-0.013
				(0.015)
Other Hospitals EHR	-0.008	0.009	0.006	0.028**
	(0.012)	(0.013)	(0.013)	(0.013)
Other Hospitals EHR (t-1)		-0.009	-0.006	-0.013
		(0.013)	(0.015)	(0.015)
Other Hospitals EHR (t-2)			-0.009	-0.001
			(0.015)	(0.017)
Other Hospitals EHR (t-3)				0.004
				(0.016)

Hospital Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	11,298	9,684	8,070	6,456
Adj. R-squared	0.341	0.319	0.284	0.234

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, Focal hospitals EHR
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Spillovers by IDS and non-IDS hospitals

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals EHR in IDS	-0.020	-0.023	-0.032*	-0.060***
	(0.014)	(0.017)	(0.018)	(0.021)
Other Hospitals EHR in IDS (t-1)		0.004	0.006	-0.006
		(0.016)	(0.017)	(0.016)
Other Hospitals EHR in IDS (t-2)			-0.006	-0.004
			(0.018)	(0.019)
Other Hospitals EHR in IDS (t-3)				0.018
				(0.020)
Other Hospitals EHR not in IDS	0.027***	0.016	0.008	0.020
	(0.010)	(0.012)	(0.013)	(0.014)
Other Hospitals EHR not in IDS (t-1)		0.012	0.004	-0.001
		(0.011)	(0.013)	(0.014)
Other Hospitals EHR not in IDS(t-2)			0.006	-0.003
			(0.014)	(0.019)
Other Hospitals EHR not in IDS (t-3)				0.013
				(0.016)
Hospital Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	11,298	9,684	8,070	6,456
Adj. R-squared	0.341	0.319	0.284	0.234

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, Focal hospitals EHR
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.4.3 Urban and Rural HSAs

Patient health and information sharing mechanisms both rely on patient mobility across the hospitals. Our data covers the whole United States and use public data sources, and therefore it is not feasible to have direct information on patient sharing at this scale. However, we test the premise of patient sharing using regional characteristics that makes it more likely for patients to be mobile across hospitals. First, urban locations have higher population density and therefore the chances for patients to move across hospitals are higher. We test whether the spillover effects are stronger in urban vs rural HSAs by interacting the neighboring hospitals' EHR adoption with an Urban HSA dummy (Table 10). Therefore the baseline coefficients on "Other hospitals EHR" represent the spillover effects in rural areas. The interaction terms between "Other hospitals EHR" and Urban dummy represents the difference in spillovers in urban areas compared to rural areas. We find that there are significant spillovers in both rural and urban areas and these spillovers are stronger in urban locations than rural locations. These results suggest that patient mobility can facilitate higher regional spillovers as shared patients create the link among hospitals.

Table 11: Spillover Effects by Urban vs Rural HSAs
DV: Log costs of focal hospital

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals EHR * Urban	-0.070***	-0.078***	-0.098***	-0.100***
	(0.020)	(0.030)	(0.030)	(0.030)
Other Hospitals EHR (t-1) * Urban		0.012	0.033	0.019
		(0.032)	(0.033)	(0.032)
Other Hospitals EHR (t-2) * Urban			-0.018	0.013
			(0.031)	(0.040)
Other Hospitals EHR (t-3) * Urban				-0.029
				(0.035)
Other Hospitals EHR	-0.034***	-0.011	-0.008	-0.006
	(0.010)	(0.013)	(0.012)	(0.012)
Other Hospitals EHR (t-1)		-0.029**	-0.008	-0.006
		(0.014)	(0.016)	(0.016)
Other Hospitals EHR (t-2)			-0.037***	-0.017
			(0.014)	(0.016)
Other Hospitals EHR (t-3)				-0.031**
				(0.013)
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

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, Focal hospitals EHR
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.4.4 Hospital Density in the HSA

As a measure of the hospital density in the area, we calculated the average distance between hospitals in the HSA by using the latitudes and longitudes of the hospitals' locations. If the hospitals are closer to each other in the area, we expect more patient sharing to occur among them as it would be easier for patients to visit different hospitals. As the hospitals are more densely located, the average distance between the hospitals in the HSA is going to be lower. Therefore, we use negative of the average distance among hospitals as a measure of hospital density. Table 11 presents the results where we interact the neighboring hospitals' EHR adoption with the negative of average distance between hospitals. We find stronger spillover effects in the HSAs where hospitals are more densely located, supporting evidence for patient sharing enabling spillovers.

Table 12: Spillover Effects by Distance among Hospitals
DV: Log costs of focal hospital

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals EHR *Neg distance	-0.006***	-0.003*	-0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Other Hospitals EHR (t-1) * Neg distance		-0.004**	-0.003	-0.003
		(0.002)	(0.002)	(0.002)
Other Hospitals EHR (t-2) * Neg distance			-0.004**	-0.002
			(0.002)	(0.002)
Other Hospitals EHR (t-3) * Neg distance				-0.004**
				(0.002)
Other Hospitals EHR	-0.078***	-0.043***	-0.039***	-0.033**
	(0.011)	(0.014)	(0.014)	(0.014)
Other Hospitals EHR (t-1)		-0.047***	-0.015	-0.015

		(0.015)	(0.017)	(0.017)
Other Hospitals EHR (t-2)			-0.061***	-0.027
			(0.015)	(0.018)
Other Hospitals EHR (t-3)				-0.055***
				(0.016)
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	0.565	0.539	0.508	0.479

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, Focal hospitals EHR
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.5 : Results: Spillover Effects by Regional EHR Dispersion

Since externalities could depend on the structure of the network, we expect the impacts to differ by how EHR technologies are distributed in the region (i.e., how many of the region's hospitals have different levels of EHR). The question we are interested in is whether the magnitudes of spillover effects are influenced by the distribution of EHR adoption in the region. Specifically, do all the hospitals need to have the same advanced level of EHR adoption to realize benefits for the region, or can significant spillover benefits be achieved even when only some hospitals specialize in advanced EHRs? This question has public policy implications because it is not only very costly but also challenging to implement EHR systems, as they require significant restructuring of hospitals' practices and training of employees. If all hospitals have to adopt the same level of EHR to achieve regional benefits, this would justify the costly process of enforcing all health care providers to adopt EHR in a given period, as the HITECH Act does. If, however, it is found that not all hospitals have to invest in same level of EHR to achieve optimal regional results, then policies can focus on prioritizing some hospitals' EHR investments as a start and develop a longer-term plan in which all hospitals adopt EHR eventually to ensure smoother and more cost-efficient transition. In light of the mechanisms that could lead to spillovers, we argue that better patient health at the time of admittance to the second hospital when a patient transfers does not require the two hospitals to have same EHR adoption level, as the improved health is caused by the EHRs (and thus high quality of care received) at the first provider. However, spillovers via better information availability about the patient should be stronger if two hospitals both have similar EHR systems. Overall, these discussion suggests that not all hospitals have to have same level of EHR to achieve cost savings in the region, however, it is not as clear whether the spillover benefits will be stronger when EHR adoption is equally distributed or not. Spillover effects due to information sharing would increase when more hospitals adopt advanced EHRs (i.e., more equally distributed). We performed the following empirical test to study how regional distribution of EHR investments moderates the spillover effects of EHR adoption.

To measure the dispersion of the EHR adoption in the region, we calculated the Gini coefficient of the EHR adoption of the different hospitals in the HSA. The Gini coefficient measures the distribution of different levels of EHR adoption among the hospitals in a HSA. It varies between 0 and 1, 0 indicating perfect equality and 1 indicating perfect inequality. For example, if there are two hospitals in a HSA and both hospitals adopt all five EHR systems, it is an example of perfect equality with a Gini coefficient of 0. On the other hand, if one of them does not have any of the EHR systems, and the other one has adopted all five EHR systems, the Gini coefficient would be 1 indicating perfect inequality among the hospitals. As the Gini coefficient increases, the distribution becomes more unequal within a HSA. We could interact directly the Gini coefficient and the focal hospital's EHR adoption level, but it is well known that it is difficult to interpret the interaction effects of two continuous variables. More importantly, the complexity would not have helped to address our question of interest. Therefore, instead of treating regional distribution of EHR investments as a continuous variable, we created a "Unequal" dummy variable that is equal to 1 if the Gini coefficient in the HSA is greater than or equal to 0.5 (and =0 if Gini <0.5), indicating a high level of uneven distribution of EHR adoption across hospitals. In short, this dummy variable categorizes each HSA as more equally (Unequal=0) or less equally (Unequal=1) distributed in terms of EHR adoption. Necessary insights to answer our research question could be obtained through the interaction of this dummy variable and the EHR adoption. Note that we also controlled for the EHR adoption level of the focal hospital as well as other hospitals in the HSA for all specifications, and therefore accounted for differences in the distribution that could have been due to different levels in the area.

Our goal is to test whether the distribution mediates the spillover effects of EHR adoption. Table 12 represents the results of the impact of EHR distribution among different hospitals in a HSA on the spillovers of the focal hospital. In column 1, we include the Unequal dummy variable in the spillover regression, and in column 2, we add interaction term between EHR adoption level and Unequal variable. The interaction between the Unequal dummy and EHR adoption is negative and significant, suggesting that a hospital with a high level of EHR adoption would have even stronger spillover effects when it is located in a region with a more unequal distribution of EHR. That is, a region with unequal distribution of EHR adoption benefits more from a hospital with high EHR adoption level, because there are some hospitals with low level of EHR adoption, which can benefit from the more advanced hospital. In sum, we found evidence that it is not necessary to have all hospitals invest in the same level of advanced level EHR system to achieve the maximum spillover effects in the region at least in the short term. Having a concentrated EHR distribution in some hospitals can be sufficient for achieving cost reductions at a regional level.

In columns 3 and 4, we separate the total EHR and the distribution of EHR in the area, into basic EHR and advanced EHR components and found that for both basic and advanced EHR systems, there is a significant and negative interaction between the adoption level and unequal variable. Our results support that not all hospitals have to invest at the same level to achieve regional cost savings, and moreover regional cost savings can be stronger when hospitals are in different stages of EHR adoption. These results have important public policy implications for the HITECH Act that imposes penalties on hospitals that do not comply, which we elaborate in the Discussion section.

Table 13: Effect of dispersion of EHR adoption on the spillovers

DV: Log costs the other hospitals except the focal				
VARIABLES	(1)	(2)	(3)	(4)
EHR	-0.021***	-0.006		
	(0.005)	(0.005)		
Unequal (HSA EHR)	0.000	0.019***		
	(0.003)	(0.004)		
Unequal (HSA EHR) * EHR		-0.044***		
		(0.007)		
Basic EHR			-0.007*	0.009**
			(0.004)	(0.004)
Unequal (HSA Basic EHR)			0.005**	0.020***
			(0.002)	(0.003)
Unequal (HSA Basic EHR)* Basic EHR				-0.031***
				(0.005)
Advanced EHR			-0.014***	-0.011***
			(0.003)	(0.003)
Unequal (HSA Advanced EHR)			0.014***	0.022***
			(0.003)	(0.004)
Unequal (HSA Advanced EHR)* Advanced EHR				-0.017***
				(0.006)
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	0.689	0.690	0.690	0.691

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:
Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees

HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.6 Additional Tests

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. First, we assessed the likelihood of alternative explanations that may be responsible for the results. Second, we addressed reverse causality using timing of changes in EHR adoption and costs. Third, we conducted a falsification test to examine if the observed spillover effects arise spuriously. Finally, we checked the robustness of our results by using different measures and conducted sensitivity analyses of our results to hospitals with missing values.

2.4.6.1 Alternative Explanation: Addressing Patient Selection

If more complex patients select into hospitals that have higher EHR investments, this can leave the rest of the hospitals in the area with a less costly patient pool. This scenario offers 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 addressed this issue in two different ways. First, we controlled for the case mix index (CMI) that measures the overall complexity of patients in hospitals. Ideally, we would have liked to do this in our main analysis, but the CMI variable is missing for several hospitals. Since we are conducting a regional level analysis, it is important to maintain a good representation of the HSAs. Therefore, we add CMI in our analysis as a robustness check. In the specifications where we controlled for focal hospitals' and surrounding HSA hospitals' CMI, similar results were found. This finding provides evidence that CMI index is not driving the cost differences after EHR implementation.

Second, and as a more direct test of this alternative explanation of patient selection, we tested whether EHR adoption affects the CMI of the focal hospital and surrounding hospitals. Specifically, we want to know if EHR adoption leads to increase in CMI of the focal hospital and decrease in CMI in surrounding hospitals. In column 1 of Table 13, 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, where we also 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 repeated similar exercises using outpatient charges, which can also be an alternative proxy for the patient profile treated by the hospital. When we controlled for the outpatient charges, our results remained similar. In columns 3 and 4 of Table 13, 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 analyzed a similar relationship between EHR adoption and patient composition, and found that patient acuity and payment per discharge were essentially the same between EHR adopters and non-adopters.

Table 14: Effect of EHR adoption on complexity of patients

	(1)	(2)	(3)	(4)
DV	CMI of focal hospital i	CMI of other hospitals in the HSA h-i	Outpatient charges of focal hospital i	Outpatient charges of other hospitals in the HAS h-i
Focal Hospital's EHR	-0.012***	0.005	-0.005	0.022
	(0.005)	(0.004)	(0.009)	(0.015)
Focal Hospital's EHR (t-1)	0.002	0.001	0.012	-0.014
	(0.005)	(0.004)	(0.011)	(0.020)
Focal Hospital's EHR (t-2)	-0.007	-0.004	-0.009	0.009
	(0.005)	(0.004)	(0.012)	(0.015)
Focal Hospital's EHR (t-3)	-0.005	0.000	0.000	0.002
	(0.006)	(0.005)	(0.013)	(0.015)
Focal Hospital's EHR (t-4)	-0.003	-0.004	-0.008	0.012
	(0.006)	(0.005)	(0.013)	(0.015)
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	0.706	0.812
Hospital Level Controls for the focal hospital and for the other hospitals in the HSA: Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees				

HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income *Other Regional Level Controls:* Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county Standard errors in parentheses. Standard errors are two-way clustered by hospital and year. *** p<0.01, ** p<0.05, * p<0.1

2.4.6.2 Timing of Changes in EHR adoption and costs: Addressing Reverse Causality

In our main results we find that the past levels of neighboring hospitals' EHR adoption affect the current levels of focal hospital's costs, which suggests that changes in costs follow changes in EHR adoption. We additionally test if the lead of EHR adoption is significantly associated with the current cost levels. If there is such significant relationship, it would provide evidence for presence of reverse causality, suggesting that costs today can affect the future level EHR adoption of neighbors. Table 12 presents the results where we include the one-year lead of the neighboring hospitals' EHR adoption and we find that this term is not statistically significantly correlated with the current costs of the focal hospital. Combining this with the significant lagged effects of EHR adoption suggest that changes in costs follow the changes in neighbor's EHR adoption and not the other way around, thus supporting a causal direction from EHR adoption to costs.

Table 15: Lead EHR adoption and spillover effects

VARIABLES	(1)	(2)	(3)	(4)
Other Hospitals EHR (t+1)	0.008	0.008	0.010	0.010
	(0.011)	(0.010)	(0.010)	(0.010)
Other Hospitals EHR	-0.053***	-0.038***	-0.042***	-0.040***
	(0.012)	(0.014)	(0.014)	(0.014)
Other Hospitals EHR (t-1)		-0.016	0.005	0.005
		(0.014)	(0.015)	(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

Hospital Level Controls for the focal hospital and for the other hospitals in the HSA:

Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, Focal hospitals EHR
HSA Level Controls: Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income
Other Regional Level Controls: Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county
Standard errors in parentheses. Standard errors are two-way clustered by hospital and year.
*** p<0.01, ** p<0.05, * p<0.1

2.4.6.3 Falsification Test: Addressing Spurious Correlation

In Table 15, we analyzed the relationship between EHR adoption and costs of hospitals located on the East Coast and the West Coast as a falsification test. We matched each hospital located in an East Coast state to a randomly selected HSA in a West Coast state (and vice versa). Patients can certainly be mobile beyond a HSA, however we do not expect this to extend to the other side of the country in any significant way. If we found a significant correlation between EHR adoptions of hospitals on the East Coast and costs of hospitals on the West Coast (and vice versa), this would have suggested that there could have been a spurious correlation problem that is not related to spillover effects. In our falsification test, we did not find any significant relationship between the EHR adoption and costs of hospitals that are located on the other side of the country, providing some assurance that our observed spillover effects are not due to any spurious correlation.

Table 16: Falsification Test

DV: Log costs of focal hospital					
VARIABLES	(1)	(2)	(3)	(4)	(5)
Other Hospitals EHR	-0.010	-0.019	-0.026	-0.026	-0.020
	(0.018)	(0.020)	(0.019)	(0.019)	(0.019)
Other Hospitals EHR (t-1)		0.011	0.011	0.009	0.000
		(0.020)	(0.023)	(0.023)	(0.022)
Other Hospitals EHR (t-2)			0.008	0.024	0.026
			(0.021)	(0.023)	(0.023)
Other Hospitals EHR (t-3)				-0.026	0.000
				(0.020)	(0.024)
Other Hospitals EHR (t-4)					-0.026
					(0.024)
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	9,195	8,582	7,969	7,356	6,743

Adj. R-squared	0.390	0.361	0.327	0.279	0.224
Hospital Level Controls for the focal hospital and for the other hospitals in the HSA: Log number of discharges, Log bed admittance days, Log Number of Beds, Log Number of Employees, Focal hospitals EHR *HSA Level Controls:* Percent residents Age 25 and younger, Percent residents 65 years and older, Percent high school graduate, Percent college graduate, Percent African American population, Percent White population, Log Total Population, Log Median Household Income *Other Regional Level Controls:* Ratio of IT firms in the county, Log Average Nurse Salaries in State, Number of Top 100 universities in county Standard errors in parentheses. Standard errors are two-way clustered by hospital and year. *** p<0.01, ** p<0.05, * p<0.1					

2.4.6.4 Additional Robustness Checks

The first additional robustness check we conducted was to use a different regional unit to calculate the spillover effects. The spillovers can manifest themselves through patient mobility that can certainly go beyond a HSA. We selected HSA for our main analysis since it was the most granular and well-defined health care market unit. As a robustness check, we conducted analysis to calculate the spillover effects at the (a) county level and (b) hospital referral region level, and our results remained qualitatively similar.

Second, underwent a robustness test regarding the treatment of the missing observations at the hospital-level, operational cost variable. Since our main goal was to estimate a regional spillover effect and not hospital level effects, we needed 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 3 years of missing observations in the 15-year panel in order to have a good representation of the hospitals in the HSAs. As a robustness test, we repeated our analysis where we used different methods or different cutoffs for the missing values and our results remain robust. This further assures that our results are not driven by treatment of missing values and we are confident about the significant spillover effects that are created by EHR usage.

Third, we have identified regional spillovers with an alternative empirical specification where we use focal hospital EHR adoption as the main independent variable and the neighboring hospitals' costs except the focal hospital as the dependent variable. We find significant spillovers in this specification.

2.5 Discussion

2.5.1 Key Findings

The goal of this research is to theorize and estimate the degree of externality (spillover effects) that EHR adoption has on a regional network of hospitals. Understanding the spillover effects helps shed light on the question of whether EHR adoption leads to reductions in health care 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. We found that adoption of one more EHR system in a hospital is associated with a 1.8 percent increase in its own costs in the current year and a cumulative effect of 2.3 percent increase in costs over four years. Similar adoption of one more EHR system in a focal hospital corresponds to 1 percent decrease in the total costs of the other hospitals in the same HSA in the initial year that carries onto the subsequent year and a cumulative effect of 1.5 percent decrease in four years. Back of the envelope calculations using our estimates indicates 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 health care costs, leading to a net cost reduction of around \$18 billion.[5] Additionally, we found evidence that both basic and advanced EHRs can contribute to regional cost spillovers. The spillovers are stronger when more hospitals are in HIE and IDS networks providing evidence for

---

[5] In this back of the envelope calculations we use average estimated cost of EHR adoption as \$14,500 per bed, and annual maintenance cost of \$2,700 per bed (CBO, 2008). 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 2033 hospitals).

information sharing mechanism. We also find evidence that the spillover effects are stronger in urban areas with higher population density and areas with higher hospital density supporting the spillovers are driven by patient sharing. We further tested whether the effects differ by the distribution of EHR investments among co-located hospitals. Results suggest that hospitals in a HSA do not need to have same level of advancement of EHR applications for regional health care cost reductions to materialize, and aggregate savings can be obtained by concentration of advanced EHRs in some hospitals, rather than EHR adoption in every hospital.

2.5.2 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. The evidence on the effects of EHR adoption on health care costs have been characterized by mixed results (Agha 2014; Dranove et al. 2012). Additionally, most of the preexisting EHR research focuses on the hospital level cost effects. We propose that regional level analysis can provide a societal perspective to gain insights on macroeconomic impacts of EHR adoption. Combining the IT productivity spillovers and hospital network literatures, we suggest that EHR adoption of a hospital can affect costs of the neighboring hospitals through shared patients, and such spillover effects were empirically quantified in this study.

Healthcare and medical literatures report that health care 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 (Fisher et al. 2009; Fisher et al. 2007; Lewis 1969; McPherson et al. 1981; Welch et al. 1993). These literatures have documented significant variations in health care delivery and costs across regions and have attempted to understand the factors affecting these local variations (Adler-Milstein et al. 2009, Giannoni et al. 2009, Phelps 1992, Wennberg et al. 1973; 1977, Wennberg 1984). Research initiatives combining data from several sources provide information on how health care resources are distributed within the US such as Dartmouth Atlas of Health Care. This regional health care map clearly indicates that health care resources are highly localized in the US. Given the nature of the health care system, and the focus of government policies at the regional level, we believe it is important to integrate this regional perspective into the economic impacts of health IT research. Even though several studies mention these potential externalities, not many of them provide theory and evidence regarding the regional impacts. We are also not aware of any empirical research trying to quantify the level of externality of EHR adoption. We aim to contribute to the preexisting literature by providing theoretical arguments and empirical evidence on the regional 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. Health care costs remain to be one of the most important policy challenges in the US. Health IT has also taken a significant role in US health care policy, and it has been subject to a big debate. HITECH Act devotes around $19 billion to provide incentives to health care providers for EHR adoption, and there have been ongoing debates among policy makers whether the benefits of EHR investments compensate the costs. Empirical evidence based on hospital level analyses of the impacts of EHR adoption on health care costs are mixed. The mixed findings increase the skepticism about the perception that EHR is a means to reduce health care costs. From a policy perspective, this also suggest that EHR adopting hospitals may not be internalizing the potential benefits of improvements in health care quality, and as a result, hospitals may have insufficient incentives to further invest in health IT.

If there are regional externalities of EHR adoption, hospital level studies can underestimate the societal impacts of such health IT investments. We provide evidence that an increase in EHR adoption is associated with higher level of costs for the adopting hospital initially, but it benefits other hospitals in the same HSA by lowering their operation costs. Altogether, there is an overall cost reduction at the society level resulting from EHR adoption. This provides a reconciliation of the mixed findings on effectiveness of EHR adoption on health care costs when regional spillover effects are considered. Since the geographical 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. These findings indicate that policy makers should account for the spillover effects and consider that expected benefits could be realized in other co-located hospitals.

We also found that the strength of the regional level spillover effects can depend on distribution of the EHR adoption in the region. Results indicate that not all hospitals in a HSA have to be on the same level of sophisticated EHR adoption level to achieve regional cost reductions. Instead, EHR adoption that is concentrated in a few hospitals can stimulate the savings in the area. Availability of advanced EHRs in some hospitals in the region can enable patients and other non-adopting hospitals in the area to benefit from these technologies. This has implications for the HITECH Act, which not only provides financial subsidies for EHR adoption, but also imposes penalties for not complying. There is a current debate around this issue as there are opposing views on the costs and benefits of EHR. The question of whether all hospitals require same level of advanced EHRs has important public policy implications because it is not only very costly but also challenging to implement EHR systems as they require overall restructuring of hospitals' processes, practices and systems. Training of doctors and staff is another difficult task that can slow down services and care. While over the long run having all hospitals adopt all the EHRs is beneficial because it increases health care quality, it can be very costly to enforce a blank policy in a given short period of time because hospitals have different acceptance and use of technology, and the costs of forcing a hospital which is not ready to adopt certain EHRs right away can outweigh the benefits. In fact, our results suggest that cost savings can be stronger when hospitals are in different stages of adopting EHRs. In other words, policy makers can focus on prioritizing some hospitals' investments as a start and develop longer-term plans in which all hospitals eventually adopt EHR systems to ensure a smoother and more cost efficient transition by leveraging the skills and know-how from early adopters.

2.5.3 Implications for Hospital Managers

Our results have implications for hospital managers and operator's decision making. Our results indicate that there can be spillovers of EHR adoption among the hospitals especially when they can share information. These findings emphasize the importance of the heath data interoperability. The hospitals that are in the same HIE and IDS can coordinate together to make sure their systems and data are interoperable to facilitate better coordination care. Additionally the hospital managers can develop mechanisms to make sure the data is not locked and shared easily with the other hospitals at least in the same HIE and IDS networks. Also given the spillover effects, it makes sense to coordinate several hospitals' decisions together. The idea of externalities can also apply beyond EHR investment and could extend to other mechanisms that facilitate information sharing among the hospitals.

2.5.4 Limitations and Future Research

This study has certain limitations that create interesting opportunities for future research. The spillover effects of EHR adoption on regional health care costs can be attributed to at least two mechanisms: improved patient health and better records and information availability. We provide evidence on the spillover mechanisms via analyses on HIE, IDS, and regional characteristics such as urban vs rural HSAs and average distance between hospitals in the area. On the other hand, we use national public data sources to combine information on the EHR adoption, costs, and other characteristics of hospitals and we are not able to observe number of patients shared across hospitals, which would require patient level data and more detailed hospital level data. However, this information could be possible to obtain for a smaller geographical unit rather than at the national level, such as in a given state. Future research can explore the magnitudes of different spillover mechanisms with such data, which would have important public policy implications. Second, we are not able to observe the extent and intensity of EHR use in the hospitals and therefore we identify the regional spillover effects based on EHR adoption. We expect the results to be stronger if EHR use can be observed instead of the EHR adoption and therefore we interpret our findings as the lower bound of potential health IT spillovers. Data on EHR use can enable estimating the spillover effects more accurately.

Endogeneity is a key empirical challenge when studying the economic effects of EHR adoption, as the adoption of these technologies is not random. We used many approaches to address the endogeneity, and each has its own underlying assumptions. More complex patients selecting into hospitals that have higher EHR adoption levels can be a potential explanation for our findings. To address this potential endogeneity 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 examined the possibility of a potential spurious correlation problem with a falsification test, where we did not find a significant relationship between EHR adoption and costs among distant hospitals. However, there could be other alternative explanations that we have not thought of.

2.5.5 Concluding Remark

The high cost of healthcare provisions continues to be one of the major policy concerns in the US, and EHR are 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 health care costs can be seen as a regional 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 surrounding hospitals in the same regional network, which is consistent with previous research arguing that hospitals can affect each other’s outcomes through shared patients. Our findings provide evidence supporting the effectiveness of EHR adoption on reducing societal health care costs and establish that the macro and micro level relationship between EHR adoption and health care costs can be different. Policy makers should also consider the characteristics of the location and the distribution of health IT among hospitals in the area to achieve the maximum level of benefits from EHR subsidies.

CHAPTER 3 : DOES THE ADOPTION OF ELECTRONIC MEDICAL RECORD SYSTEMS INFLATE MEDICARE REIMBURSEMENTS?

Despite their many touted benefits, Electronic Medical Record (EMR) systems have been argued to make it easier for physicians to inflate the complexity of patients' diagnoses to artificially boost reimbursements from insurers (termed "upcoding"). In this paper, we examine if the adoption of a particular EMR module, the Computerized Physician Order Entry (CPOE) system that allows physicians to use default templates and reuse information from a previous patients' chart when recording a patient's diagnosis, is associated with an increase in the case mix (aggregate complexity of all patients' diagnoses in a given hospital) that hospitals report to Medicare. In this study, we leveraged the implementation of the Recovery Audit Program that aims to combat inappropriate Medicare reimbursements as a quasi-natural experiment. We found that on average, the adoption of CPOE systems is associated with an increase in the reported case mix by hospitals. The inflated case mix corresponds to an excess $300 million per year in Medicare reimbursements. Also, the increase in the case mix after CPOE adoption is significantly stronger for for-profit hospitals. However, the adoption of the Recovery Audit Program attenuates the role of CPOE systems in inflating the case mix that hospitals report to Medicare, thus helping to combat upcoding and auditors who develop capabilities to identify the use of copied information are able to moderate the effect to a greater extent. Implications for theory, practice, and public policy toward preventing inflated Medicare reimbursements from taxpayers' dollars after the introduction of CPOE systems are discussed.

3.1 Introduction

The adoption of Electronic Medical Record (EMR) systems in hospitals in the United States (US) has been rapid in the last decade. While 13% of hospitals had systems that would enable them to store clinical data electronically in 1996, about 80% of hospitals had this capability by 2009 (Dranove et al. 2012). Considering the widespread adoption of EMR systems, it is important to fully understand their effects on the costs and quality of healthcare services. The increase in EMR adoption has been spurred by the HITECH Act that provides $27 billion in subsidies to hospitals to adopt EMR systems and penalizes the hospitals that do not comply. The justification behind this policy is that EMR systems would reduce health care costs and improve quality via reductions in inefficiency, medical errors, inappropriate and unnecessary care (US Congress 2009, p. H. R. 1—116). However, anecdotal reports have suggested that these systems may instead by used to inflate the complexity of the diagnosis of patients (termed "upcoding") to increase the hospital's reimbursements from Medicare (Abelson et al. 2012).[6] In this study, we examine if one of the unanticipated impacts of the adoption of EMR systems is their use by hospitals to strategically increase their revenue.

The main EMR system that allows physicians to electronically record a patient's diagnosis is the Computerized Physician Order Entry (CPOE). This system enables physicians to enter, store, and share patient data, electronically order medications and tests to pharmacies and laboratories. However, CPOE systems provide users default templates that make adding extra information into a patients chart easier as well removing information costly. They can also allow physicians to reuse previous patients' information when recording a patient's diagnosis. This additional information can be used to legitimize a more complex diagnosis and thus a higher reimbursement rate. Abelson et al. (2012) gives the example of two hospitals: Faxton St. Luke's Healthcare in Utica, N.Y. where patients in the category with the highest level of

[6] Medicare is social insurance program in the United States of America. The plan is primarily tasked with providing insurance to people aged 65 and over and individuals with certain disabilities. In 2011, the program insured 48.7 million people in the US and covered 47.2% of inpatient hospital costs (Torio et al. 2013)

reimbursement increased 43% the year they adopted EMR systems, and Baptist Hospital in Nashville where reimbursements in the highest level climbed 82% the year after it started using EMR systems for patient record documentation. Due to these and many other anecdotal cases, in 2012 the former Secretary of Health and Human Services, Kathleen Sebelius and former attorney general Eric Holder Jr. warned hospitals to refrain from unethically using EMR systems to facilitate upcoding. Their letter noted that the practice of upcoding is illegal, and that hospitals should not submit false documentation to artificially boost their Medicare reimbursements (Reed et al. 2012). Similarly, insurers have issued similar warnings to hospitals. A Medicare administrator, the National Government Services (NGS) warned doctors against the practice of "cloned documentation," informed them that it could lead to denial of service and other severe penalties (Yale Medical Group 2012).

The adoption of CPOE systems by hospitals and the observed increase in reimbursements coincided with a staggered rollout of the Recovery Audit Program across the U.S. This program was initially implemented in 2005 in the states of California, Florida, and New York. The program uses 'recovery auditors' to examine hospital data and identify overpayments, aiming to recover $2 billion in overpayments by 2012 (Anderson et al. 2015). These recovery auditors were specifically tasked with identifying "[if the] submitted service was upcoded" (Centers for Medicare & Medicaid Services 2015b). After the pilot audit identified $900 million in overpayments to Medicare, the Recovery Audit Program was eventually expanded to all 50 US states, and it continues today (please see Appendix A for more details about the Recovery Audit Program). However, one of the main issues that auditors correct in billing in the submission of upcoded bills and the program presents an interesting quasi natural experiment that could moderate the effect of upcoding.

There is little previous research that examined the effect of the adoption of EMR systems on upcoding. The few studies on this relationship find differing results. Adler-Milstein et al. (2014) found that the adoption of EMR systems is not associated with upcoding. On the other hand, Li (2014) found evidence that the EMR adoption is associated with upcoding. In this paper, we examine the direct impact of the adoption of CPOE systems on reimbursements to hospitals. Further, test the effect of moderating factors such as the presence of the Recovery Audit Program and type of hospital (for-profit vs non for-profit) to examine where the effect may or may not exist.

We use various data sources such as HIMSS and the Medicare Inpatient Prospective Payments Systems files to create a hospital panel from 2004 to 2011 to examine the relationship between CPOE adoption and case mix of hospitals (average complexity of patient diagnosis). For our identification strategy, we used a hospital fixed effects model and leveraged the Recovery Audit Program as a quasi-natural experiment. We used proprietary data obtained by filing a Freedom of Information request on the capabilities of auditors to identify copied and over-documented records to examine how auditors attenuate the ability of CPOE systems to facilitate upcoding. We found that on average there is a positive relationship between CPOE adoption and case mix of hospital. This positive relationship disappears when hospitals are covered by the Recovery Audit Program. We also found that the effect of CPOE on case mix is significantly higher among for-profit hospitals that provide higher incentives for practicing upcoding. The presence of the audit program and type of hospital are key moderators for the relationship between CPOE adoption and upcoding, which are potential explanations for the mixed results in prior studies. In addition, we make use of the audit program as a quasi-natural experiment to rule out alternate explanations that CPOE systems may allow physicians to better code their patients and that the systems may be attracting patients with more complex diagnosis to the hospitals with CPOE systems. We also used an Instrumental Variables approach, a Latent Instrumental Variable (LIV) model, propensity score matching, and a relative time model that test pre- and post-treatment effects to address potential endogeneity concerns. Our results are robust to these alternative tests and specifications.

In terms of economic effects, we found that the adoption of CPOE systems is associated with a significant increase in the case mix of hospitals that corresponds to an average of about $167,390 of inflated reimbursements to Medicare for each hospital each year. For-profit hospitals average $369,667 in inflated Medicare reimbursements, and not for-profit hospitals average about $154,745 in inflated reimbursements. This amounts to over $302,000,000 per year in excessive taxpayer dollars, on average, in our sample. Still, the Recovery Audit Program has been effective in attenuating the increase in Medicare reimbursements. These results imply that policy makers need to be cognizant of the fact that EMR systems can be inappropriately used by hospitals to falsely claim inflated Medicare reimbursements. Policy makers could frame guidelines on how hospitals can use utilize EMR templates for generating patient records to reduce the inappropriate use of EMR systems. Additionally, as the Recovery Audit Program prevents hospitals from claiming inflated reimbursements, the program should be strengthened and resources must be given to auditors to develop capabilities to identify the use of templates and copied information in patient records.

3.2 Previous Research

3.2.1 Hospital Case Mix, Patient Coding, and "Upcoding"

A vital step of a physician observing a patient is recording information in the patient's medical records. This process involves the physician asking patients their symptoms, performing and interpreting examinations, arriving at a diagnosis, treatments, and then recording this information in the patient's chart. This information was traditionally recorded on paper, but EMR systems now allow patient information to be stored electronically. Information that is recorded in the patient's chart is then used to assign the patient to a Diagnosis Related Group (DRG). These DRGs are groups that describe patients that have similar conditions and require similar clinical procedures. For example, comparable patients that have all had appendectomies are placed in the same DRG. The process of assigning a patient to a DRG is known as "coding". Professional coders can only use the information on the patient's record, and they are required to strictly adhere to the information in the patient chart without using their own judgment about procedures and diagnoses that were not documented. This makes the information on the patient's chart critical to the coding process. There are several DRG systems, and we restrict our discussion to MS-DRGs (Medicare Severity Diagnosis Related Groups), given our focus and data on Medicare reimbursements.

Each patient is placed in a DRG and hospitals then compute their total aggregate "Case Mix Index" (CMI) by taking an average of the weights of the DRGs of all of their patients in the hospital.[7] Similarly, the Transfer Adjusted CMI for a hospital is the average of all the weights of the DRGs of all its patients after taking into account patients who are transferred in and out of the hospital. Overall, a higher CMI indicates that a hospital treats a more complex set of patients. Insurers such as Medicare use DRGs to reimburse hospitals and higher DRGs (and thus a higher CMI) correspond to higher reimbursement rates. All patients in the same DRG are generally reimbursed at the same amount during a year. However, there are substantial cross-DRG variations in the dollar amount that hospitals are reimbursed. For example, within the set respiratory set of DRGs in 2012, "DRG 192", a diagnosis of "Chronic obstructive pulmonary disease without C[omplications or] C[o-morbidities]/M[ajor] C[omplications or] C[omorbidities]" gave an average reimbursement rate of $4,865, while "DRG 190," indicating a diagnosis of "Chronic obstructive pulmonary disease w[ith] M[ajor] C[complications] C[omorbidities]" was reimbursed at the rate of $7,899.98–an increase of 62% more than the base case within the set of respiratory DRGs.[8] This renders financial incentives for hospitals to upcode patients in higher DRGs to claim higher Medicare reimbursements.[9] Even small changes in the case mix can result in much higher reimbursements for hospitals, making the practice of "upcoding" patients integral to the profitability of hospitals.

[7] The average CMI is a weighted average of the complexity of all patients in the hospital. Each DRG is assigned a relative weight, which is a measure of the complexity of patients belonging to the same DRG. For example, in 2014, the DRG "Heart transplant or implant of heart assist system with major complications or comorbidities" was assigned a weight of 25.35, whereas the simpler DRG representing patients with "respiratory infections and inflammations without complications or co-morbidities" was assigned a weight of .97, indicating that patients that required a heart transplant had to have procedures that were much more complicated and costly than patients with respiratory infections and inflammations without any complications. The CMI is calculated by taking the average of all the weights.

[8] CC/MCC indicates (Major) Complications and Comorbidity conditions and indicates a serious medical issue, such as diabetes.

[9] Although the method to calculate the case mix index may change over time, the changes would need to be systematically correlated with the type of hospital to have an impact on our results.

3.2.2 Electronic Medical Record Systems

With the widespread adoption of EMR systems, research on the effects of EMR systems on hospital performance has increased, and this literature is characterized by mixed evidence. Studies have documented numerous positive effects of EMR systems on hospitals, such as reductions in the utilization of care, medical errors, and patient mortality (e.g. Bardhan et al. 2013; Bates et al. 1998; Devaraj et al. 2000; Dexter et al. 2004; McCullough et al. 2010; McCullough et al. 2016; Miller et al. 2011; Ransbotham et al. 2013; Tierney et al. 1990) and improvements in hospital productivity and performance (Atasoy et al. 2016; Lee et al. 2013). In contrast, other studies showed the adoption of EMR systems is associated with disruptions in the business processes of hospitals, and that workarounds are often required (Soh et al. 2004). Some other studies also found EMR adoption *not* to be associated with a significant improvement in the overall performance of hospitals (e.g. Agha 2014; Dranove et al. 2012).

The literature has focused on five major EMR systems: the Clinical Data Repository (CDR), the Clinical Decision Support System (CDSS), the Order Entry (OE) system, the Physician Documentation (PD), and the Computerized Physician Order Entry (CPOE) system.[10] In this study, we focus on the CPOE system as it provides templates and auto-populates patient charts that can enable upcoding. The CPOE system allows physicians to enter patient data, share this data with other healthcare providers (such as pharmacists and lab technicians) and record drug and treatment history for the patient. The system replaces traditional paper based records that were used for placing orders and communicating information among providers. While using CPOE systems, physicians have the option to select the various drugs that they

---

[10] The CDR is a data warehouse that stores patient data in real-time from a number of different clinical sources. The repository can be set up to store information about the history of patient conditions, diagnosis and treatments, demographics, as well as store images and reports that have been generated during a hospital visit. The Clinical Decision Support System (CDSS) supports physicians in making decisions regarding patient diagnosis and treatment. The system can alert physicians to possible drug interactions that may be harmful, and to side-effects of the consumption of drugs. The OE system allows physicians to co-ordinate the delivery of drugs with pharmacists. The PD system is an automated interactive system to help physicians increase the accuracy and completeness of their documentation in their patient diagnosis, and the data that they require to complete the evaluation of the patient (Nuance 2015. "Computer Assisted Physician Documentation." The PD system works by automating the workflow and enabling the input of structured data to help the physician diagnose the patient.

would like to prescribe to their patients, as well as the frequency with which they should be expected to take the drug. However, the process of ordering multiple drugs along with entering the periodicity with which the patient should take these drugs was cumbersome and time-consuming (Poissant et al. 2005). Although the adoption of CPOE is often problematic due to the need to coordination and implementation across multiple hospital units and providers, studies have shown that the CPOE adoption has several positive effects on patient treatment metrics (Chaudhry et al. 2006).

Other EMR systems (CDR, CDSS, OE, and PD) often can interact with the CPOE system. However, we do not expect them to significantly affect upcoding. These other systems predominantly feed data into the CPOE system; for example, the Clinical Data Repository (CDR) system is the database that the CPOE system is built on. Moreover, the Clinical Decision Support System (CDSS) system takes data from the CPOE system to diagnose patients better and check for medical errors. However, these other EMR systems do not generate automated data in templates and do not enable reusing past patient data, and therefore the effect of these other EMR systems on upcoding is expected to be small, or at least indirect through the CPOE system (albeit we still empirically test the effect of these other EMR systems on upcoding as a robustness test).

In sum, the ability of CPOE systems to allow physicians to upcode their patients, and for hospitals to request higher reimbursements, have raised concerns that that the systems may be used in unintended ways (Abelson et al. 2012). We aim to contribute to the emerging literature on upcoding by improving the understanding of the complex (direct and moderated) relationship between CPOE adoption and upcoding, and more broadly the unintended consequences of the adoption of EMR systems.

3.3 Hypotheses Development

3.3.1 The Default Effect & The Role of CPOE Systems in "Upcoding"

When people have to choose from a set of options, a disproportionate number of people choose the option that is set as default to them, even if the cost of switching away from the default option may be trivial

(Kahneman et al. 1982). This is known as the “default effect” (Brown et al. 2004; pp. 529). Studies have found that people who have to opt out of e-mail listservs are twice as likely to receive e-mails than when they had to opt in to receive future emails (Johnson et al. 2002), consumers who had to remove extra options in their cars ended up with more expensive cars than those that had to add options on their car (Park et al. 2000). The default effect is stronger when there are more decisions to make (Augenblick et al. 2012; Levav et al. 2010) and when the decision maker suffers from fatigue (Danziger et al. 2011). Many theoretical arguments have been proposed to explain the occurrence of the default effect (Huh et al. 2014; Park et al. 2000). One explanation for this biased response is that it takes extra cognitive and physical effort to switch away from the default option than to proceed with the default option (Johnson et al. 2002). Another explanation that has been advanced is that users anchor their decisions based on the default option and see losses when they compare other options (Kahneman et al. 1991). Overall, the default effect has been characterized by the heuristic: “If there is a default, do nothing about it” (Gigerenzer 2008).

In healthcare policy, Johnson et al. (2003) found stark differences in organ-donation rates between countries where citizens have to opt-in to donating their organs at the time of death versus those in countries where they have to opt-out. Other healthcare policy interventions have made the default option to remove urinary catheters after 72 hours to reduce the rate of infection (Cornia et al. 2003), and the screening of patients for HIV when they come into clinics (Branson et al. 2006).

CPOE systems often come with default ‘order sets’, which are predetermined sets of orders that are often prescribed together. By utilizing a default order set, the physician does not have to order the individual medications one by one – but can order the bundle for the patient together. Studies have found that the use of these order sets reduces the morbidity and mortality due to an increase in compliance with best practices (Ballard et al. 2010). Additionally, these order sets come with templates that can be used by physicians to generate a patient’s history without the physicians having to enter all information by themselves. These default ‘templates’ allow physicians to automatically generate patient record data without typing them, although the physician has the option to modify the default template. This inclusion of default information into a patient's chart is likely to change how the physician develops medical records. CPOE systems can also enable adding previously generated information easily into a new patient's record. For example, information on social history (such as alcohol and other patient's dependencies) that were stored from previous patients can be inserted into a new patients' chart by default. This would indicate that the social history was discussed at the visit when this might not have been the case, allowing the hospital to claim that a greater deal of information was ascertained during the interaction, and thus allowing them to file for higher reimbursements. CPOE systems also allow physicians to copy-and-paste examination findings from previous patients to show more detailed examination histories than actually took place, and the ability to easily check a number of boxes simultaneously to indicate that the physician conducted multiple additional tests (Adler-Milstein et al. 2014; Bukata 2013; Li 2014). For instance, a statement to indicate that additional tests were conducted (such as ear, nose and throat checkup during a regular visit) and were negative could be inserted by default even when the tests were not conducted again, thus allowing the hospital to claim higher levels of reimbursement due to higher levels of alleged care provided to the patient. Finally, the physician's notes could also indicate, by default, that patients were given a diagnosis on the treatment and prevention of certain conditions that the patient was presumably at a high risk during a visit, even when this might not necessarily have been the case for the patient. Together, if auto-generated data are seamlessly included into a patient's chart without the corresponding level of care being provided, the patient would be upcoded to increase the reimbursement for which the hospital would be eligible.

Taken together, hospitals can seamlessly inflate the reported level of care that was provided to the patient when using the default options of CPOE systems, thus resulting in higher claims for reimbursements to the hospital. In contrast to traditional paper-based records where the physician had to document the interaction with the patient in detail (thus opting-in to add the patient's information), the use of defaults in the CPOE system makes the physician opt-out from recording patient information (by having to manually delete default information from the chart rather than having to manually add patient information). In sum, extending the "default effect" theory to CPOE systems, we argue that the additional cognitive cost and effort that it takes for a physician to opt out from the default inclusion of information into a patient's chart may encourage the physician to retain the existing default information on a higher complexity of diagnoses, thus inflating the complexity (or case mix) that hospitals report of their patients, on aggregate. We thus propose the following hypothesis for testing:

H1: The adoption of CPOE systems is positively related with the case mix of a hospital.

3.3.2 The Role of CPOE Systems in "Upcoding" among For-Profit Hospitals

Hospitals ultimately are composed of two fundamentally different structures – the clinical side, which is run by physicians, and a second one that is run by hospital administrators (Harris 1977). The role of the clinical structure is to interact, diagnose, and treat patients; nonetheless, the profitability and the solvency of the hospital is the responsibility of administrators. While the clinical side of the hospital needs to allow upcoding to take place by entering the appropriate information in a patient's chart, it is ultimately the administrative side of the hospital that benefits because it directly affects the revenues of the hospital (Silverman et al. 2004). Duggan (2002) found that in for-profit hospitals, 49% of the board members are likely to be physicians against 24% for not-for-profit hospitals or 12% for public hospitals, allowing the administration to make the physicians aware of the issues that the administration faces and align the actions of the physicians with the goals of the administration. For-profit hospitals also often allow physicians to purchase equity in the hospital (Barciela 1993) to align the financial objectives of the physicians (agents) with those of the administration (principal). Gottlieb et al. (1997) documented that after the holding company of for-profit hospitals took over a hospital in Miami in 1993, 76% of the patients were coded at the highest rate – as compared to 31% the year before. By 1995, the number had jumped to 90%, as opposed to 28% of cases in a neighboring non-for-profit hospital owned and operated by the local government.

Although there is a large literature on examples and explanations of the default effect, this line of research does not focus on the default setter (that is, the actor who sets the default option). However, drawing upon the strategic communication literature (e.g. Dickhaut et al. 1995), Altmann et al. (2013)

argued that the default setter has the ability to act strategically by choosing the default option out of the choices that are provided to the decision maker. The default setters can be the government in the case of people deciding on organ donation (Johnson et al. 2003), the car retailer in the case of the customers choosing the options to add on to a car (Park et al. 2000), or the website owner selecting if the default option for web visitors is to opt into the emails that the website sends out (Johnson et al. 2002). We study how goal congruence between the default setter (hospital administration) and the decision maker (physician) can moderate the change in reported patient complexity after the adoption of CPOE systems. In the case where there is a degree of congruence of goals between the default setter and the decision maker, the selection of the default option may be chosen to a greater extent for increasing the complexity of patients. Additionally, there could be a tacit understanding that it is in the best interest of the decision maker (and the default setter) to select the default option (and at least make it easier for the decision maker to select the default option) to further the common objective of the decision maker and the default setter. We argue that the hospital administration (which primarily directs the implementation of EMR systems) has its own objectives to ensure the hospital's profitability, and for-profit hospitals have higher goal congruence between the administrative and physician structures of the hospital. This can lead to alignment of incentives in the hospital to upcode patients to achieve the hospital's for-profit goals, as noted by previous research (Silverman et al. 2004). Therefore, we propose the following moderated hypothesis for testing:

H2: The positive relationship between CPOE adoption and the case mix of a hospital is stronger among for-profit hospitals.

3.3.3 The Role of the Recovery Audit Program in "Upcoding"

In 2005, Medicare implemented the Recovery Audit Program to determine if auditors could effectively identify and adjust improper reimbursements. The program works by recovering additional payments made to service providers (such as hospitals), but at the same time allowing service providers to be reimbursed if they have been underpaid.[11] In 2013, the program identified and corrected $3.75 billion in improper payments (Centers for Medicare and Medicaid Services 2013). Initially, the Recovery Audit Program was limited to states with the highest levels of Medicare reimbursements–California, Florida, and New York–and it expanded to Arizona, Massachusetts and South Carolina in 2007. After 2010, the program was expanded nationwide with the bold goal to reduce payments errors by $50 billion and cut the Medicare fees for-service error rate in half (Anderson et al. 2015). For more details, please see Appendix A.

The Recovery Audit Program works by auditing Medicare bills that have been submitted by hospitals. The auditors use proprietary software to identify claims that might have been submitted incorrectly. The auditor can then request the hospital to provide chart data, and the auditor can use these data to adjust reimbursements. The Recovery Audit Program works as an oversight mechanism to identify and correct errors by hospitals. While research on the impact of oversight in the medical domain is limited, there is an extensive amount of scholarship of auditing in organizations. Dechow et al. (1996) found that greater oversight, which is measured by higher quality board executives, leads to a lower likelihood of financial statement frauds. Studies have found that the type of expertise of the overseer will also have an impact on the oversight that is provided (McDaniel et al. 2002). Also, audits can reduce earnings management, which is indicative of lower information asymmetry between managers and investors (Brown et al. 2007; Hunton et al. 2006). The quality of audit has also been linked to other changes in hospital operations (Venkataraman et al. 2008). This stream of research found that oversight has the potential to change the manner in which processes are carried out in organizations. Extending the literature on the effects of audit and oversight to the context of the role of the Recovery Audit Program on the propensity of hospitals to upcode patients using CPOE systems, we propose the following moderated hypothesis for testing:

H3: The positive relationship between CPOE adoption and the case mix of a hospital is attenuated by the Recovery Audit Program.

[11] In 2010, the amount of improper payments incurred from Medicare/Medicaid was estimated to be about $70 billion (GAO 2011).

3.4 Data and Empirical Strategy

3.4.1 Data

To examine the effects of CPOE adoption on the case mix of hospitals, we constructed a hospital level panel between 2004 and 2011. We used data from the Healthcare Information and Management Systems Society (HIMSS) database for the adoption of CPOE and other EMR systems by hospitals across the US.[12] A hospital was coded as having the system in a year if the system status was reported as "Live and Operational" or "To be replaced" in the database.[13] We obtained case mix information about the hospital from the Medicare Inpatient and Prospective Payment System (IPPS) files. The data contained information on the complexity of cases that the hospital treated under Medicare, and is based on the proportion of patients that belong to different DRGs that were inpatients in the hospital in a particular year. A higher case mix indicates a more complex set of patients that a hospital admitted. For our analysis, we used the TACMI (Transfer-Adjusted Case Mix index) as our main dependent variable (termed "CMI"), which accounts for transfer patients. In line with previous studies, we included a number of hospital level controls, such as the number of beds, bed admit days, discharges, and hospital employees. These data are furnished to Medicare by hospitals for their reimbursements. We also included regional demographic controls from the US Census such as age, education, income, population, and race to account for differences across counties.

The data set was constructed by selecting hospitals that have no missing EMR systems or CMI data. Missing data for the hospital operational controls were populated by using a linear interpolation for missing values in the middle of the panel and using the most current value at the end of the panel.[14] This resulted in

---

[12] Although HIMSS provides information starting in 1996, we limit our analysis to systems adoption after 2004 as the CPOE information is only provided after 2004.

[13] Communications with HIMSS indicated that the code "To be replaced" indicated that the hospital uses the system and has not completely abandoned the use of the system.

[14] If a hospital has observations missing at the end of the panel, we used the most recent values. This is to guard against extrapolating too far away from the panel. However, for observations missing that are between observed values, instead use a linear interpolation method as we are less concerned about extrapolating away from the values in the panel.

a balanced panel of 14,440 observations for 1,805 hospitals. We also dropped hospitals that abandoned their CPOE system during the period of the panel. Table 1 provides summary statistics for our final sample.

Table 17: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
CPOE	0.23	0.42	0.00	1.00
Transfer Adjusted Case Mix	1.41	0.26	0.43	3.00
CDR	0.83	0.38	0.00	1.00
CDSS	0.76	0.43	0.00	1.00
OE	0.93	0.25	0.00	1.00
PD	0.27	0.45	0.00	1.00
Other EMR adoption	0.69	0.24	0.00	1.00
For Profit (Binary Variable)	0.17	0.38	0.00	1.00
Copy Identification	0.15	0.35	0.00	1.00
Number of Employees	1799	30099	1.00	2386053
Bed Admits	42974	44769	115	616910
Number of Beds	185	205	6	17053
Number of Discharges	11117	10494	12	135352
Resident population	836657	1689132	3233	9818605
Resident population under 18 years	23.24	2.91	10.50	35.80
Resident population 65 years and over	14.00	3.41	6.60	35.10
Resident population: Black	13.67	14.08	0.20	77.80
Resident population: White	78.98	15.29	18.80	98.80
Median household income	51121	13544	20206	104914
Educational attainment - High School	84.56	6.21	56.10	98.60
Educational attainment – Bachelors	26.04	10.31	6.30	63.90
Population	836657	1689132	3233	9818605

3.4.2 Empirical Specification and Identification Strategy

Our primary goal was to identify the effect of CPOE on the case mix index of a hospital. We exploited the variation in the adoption of CPOE systems over time in hospitals and analyzed whether CPOE adoption is associated with higher levels of the case mix of each hospital. To account for time invariant heterogeneity across hospitals, we used a hospital fixed effects model. Therefore, our identification comes from within hospital changes in CPOE adoption and case mix (CMI). We introduced many hospital level characteristics and county level socio-economic control variables and time dummies into the model to control for alternate factors that could affect the case mix of the hospital. Our main estimation equation was as follows:

$$\boldsymbol{CMI_{it} = \beta_0 + \beta_1 CPOE_{it} + \beta_2 Z_{it} + \beta_3 \vartheta_{ct} + \delta_i + \gamma_t + \varepsilon_{ij}}\ [\mathbf{1}]$$

where CMi_{it} is the case mix of hospital i in year t, and $CPOE_{it}$ is dummy variable that is equal to 1 if hospital i has CPOE system in year t. Z_{it} represents hospital level controls such as the number of employees, beds, discharges and bed admit days and the average of the adoption of other EMR systems such as CDR, CDSS, OE and PD in the hospital, δ_i represents hospital fixed effects and γ_t represents time fixed effects. ϑ_{ct} represents the county level control variables for c^{th} county which the i^{th} hospital is located in. As the county level control data is cross-sectional, we multiply this by the year in order to include this in our model. Table 2 provides the list of control variables we use in our analyses.

Table 18: Control Variables

Hospital level controls	**County level controls**	**Fixed Effects**
Presence of Other EMR Systems (Average of CDR, CDSS, OE and PD)	Resident population under 18 years proportion * Year	Hospital
Log (Number of Employees)	Resident population 65+ years proportion * Year	Year
Log (Number of Bed Admit Days)	Resident population of Black proportion * Year	
Log (Number of Beds)	Resident population of White proportion * Year	
Log (Number of Discharges)	Percent high school graduate proportion * Year	
	Percent bachelors graduate proportion * Year	
	Resident population * Year	
	Median household income * Year	

The relationship between CPOE adoption and CMI has potential endogeneity issues. A statistically significant positive correlation between CPOE adoption and CMI may not indicate that CPOE systems facilitate upcoding, and there can be alternative explanations. *First*, the adoption of CPOE systems may attract more complex patients to the hospital. Research has found that the adoption of EMR systems benefits patients with more complex conditions (McCullough et al. 2016), and that patients are mobile among hospital providers within a hospital market (Huang et al. 2010; Lee et al. 2011; Wennberg et al. 2004). Hence, CPOE investments could lead to the hospital attracting more complex patients, which would increase the case mix. *Second*, CPOE systems might allow physicians to "better code" their interaction with their patients and capture more accurate information than paper based records. For example, due to check boxes in EMR systems that allow physicians to reliably code if procedures were properly carried out or not, the physician is prompted with a larger set of tests than they would have been with paper based records. Also, templates of questions that the physicians have to ask patients and get information allow physicians to capture more data without missing out vital questions. This richer interaction with the patient allows physicians and hospitals to capture more data, which can be used to file for (truly) higher reimbursements. In other words, the higher level of complexity in diagnoses after CPOE adoption might not be artificially inflated due to upcoding, but it may be a true increase due to capturing more accurate data about patients.

To address these two alternative plausible explanations of more complex (sicker) patients and better coding, we leveraged the Recovery Audit Program as a quasi-natural experiment. If the increase in CMI is real (non-inflated) due to a true change in the patient profile or due to more accurate patient data, the increase should remain when hospitals face an audit. As the Recovery Audit Program should not dissuade a hospital from attracting sicker patients or having better coding, CPOE adoption should be positively correlated with the CMI, even under the Recover Audit Program, for these explanations to hold true. However, we found that the positive relationship between CPOE adoption and CMI attenuates when a hospital faces an audit, offering empirical evidence that this relationship is not driven by increases in patient complexity or better coding, but rather an artificial inflation of the CMI. Also, we used a spillover model to test whether the patient profile changes after CPOE adoption. Under the assumption that patient characteristics in a hospital market do not change when a hospital adopts CPOE systems, a movement of patients with complex cases to the hospital with CPOE systems will decrease the complexity of patients in hospitals in the same geographical market. We empirically tested this alternative plausible explanation, and we did not find any evidence of a significant change in the patient profiles after CPOE adoption.

Third, the adoption of CPOE systems by hospitals is not an exogenous decision. This can be problem for our analysis if there are unobserved factors that drive both the CPOE adoption and the increase in the CMI, simultaneously. Therefore, confounding factors could be driving the changes in both the independent and dependent variables. To address this issue, we use two types of Instrumental Variable (IV) analyses. First, we used a Latent Instrumental Variable (LIV) approach where we used distributional assumptions to identify an instrument that is inherent in the error structure of the independent variable (Ebbes et al. 2005). The advantage of the LIV method is that it does require a defined instrumental variable and let the data to choose an appropriate instrument. Second, we instrumented CPOE adoption of the focal hopsital by the CPOE adoption of co-located hospitals and also by the availability of broadband Internet in the area, which should not be directly related to upcoding in the focal hospital. Our results remained robust to all three of these IV analyses. Additionally, if there was a confounding driving force for the adoption of EMR systems and an increase in CMI, we would expect to find similar correlations between other EMR systems and CMI. However, due to the templates that are enabled by the CPOE system, theoretically CPOE system (and not other EMR systems) could lead to an increase in the case mix. Hence, we analyzed the relationship between upcoding and another advanced EMR system, the Physician Documentation (PD) system, as a falsification test. The PD system captures discrete data that are used for interaction with the (CDSS) Clinical Decision Support System relative to evidence-based medicine guidelines and/or protocols (HIMSS 2014), and accordingly it should not directly affect upcoding. We found that PD adoption is not related to the CMI, which provides additional evidence that the observed relationship between CPOE and CMI is not spurious.

Fourth, hospitals that adopt CPOE systems may be structurally different from those that do not adopt CPOE systems, and hospitals that adopt CPOE systems have more complex patients even before they adopt these systems. To address this concern, we used a relative time model (Greenwood et al. 2015). We found no difference in the pre-adoption phase among hospitals that adopt CPOE systems, but that there is an increase in their CMI 2-3 years after adoption. Also, we used the Propensity Score Matching (PSM) analysis by matching hospitals that are similar to each other, but they differ in their adoption of CPOE systems to provide another test for the same issue. We found that among the matched groups of hospitals, CPOE adoption is associated with a higher case mix reported by hospitals, confirming our main results.

3.5 Results

3.5.1 CPOE Adoption and Upcoding

The first set of results presents the effect of the adoption of CPOE systems on CMI (Equation [1]). We found that, on average, there is an increase in the CMI when hospitals adopt CPOE system. This effect is robust across different columns of Table that stagger the inclusion of control variables. thus supporting H1.

Table 19: Effect of CPOE on Case Mix Index of a Hospital

	(1)	(2)	(3)
VARIABLES	CMI	CMI	CMI
CPOE	0.0072**	0.0073**	0.0052*
	(0.0022)	(0.0023)	(0.0022)
Other EMR systems		-0.0006	-0.0026
		(0.0032)	(0.0031)
Hospital and Time FE	Yes	Yes	Yes
Controls	No	No	Yes
Constant	1.3705***	1.3708***	10.5040
	(0.0016)	(0.0023)	(12.7490)
Observations	14,440	14,440	14,440
R-squared	0.2607	0.2607	0.2897
Number of Hospitals	1,805	1,805	1,805

Column 2 includes other EMR systems as controls and column 3 includes other control variables listed in Table 2. Standard errors are clustered by hospital and year. Table B1 in the Appendix shows the results were robust when we de-aggregated the other EMR systems control variable. Results are robust to dropping outliers as shown in table B3 in Appendix.

**** p<0.001, ** p<0.01, * p<0.05*

3.5.2 CPOE Adoption and Upcoding among For-Profit Hospitals

We tested whether the proposed positive relationship between CPOE and CMI (H1) is more pronounced for for-profit hospitals (H2) where the incentives are more aligned to report a higher case mix (Table 4). We found that the relationship between CPOE adoption and upcoding is statistically stronger among for-profit hospitals, thus supporting H2. Columns 3 and 4 (Table 4) disaggregate the sample into for profit and non for-profit hospitals and we find that the effects existis prevelant on average for for-profit hospitals.

Table 20: Effect of CPOE on Case Mix Index

	(1)	(2)	(3)	(4)
VARIABLES	CMI	CMI	CMI	CMI
	All Hospitals	All Hospitals	For Profit Hospitals	Non For-profit Hospitals
CPOE	0.0052*	0.0029	0.0207*	0.0031
	(0.0022)	(0.0023)	(0.0092)	(0.0023)
CPOE * For Profit		0.0247**		
		(0.0092)		
Hospital and Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Presence of other EMR systems	Yes	Yes	Yes	Yes
Constant	10.5024	11.0555	1.0245	19.8080
	(12.7486)	(12.7277)	(38.9857)	(13.9567)
Observations	14,440	14,440	2,520	11,920
R-squared	0.2897	0.2914	0.3020	0.2929
Number of Hospitals	1,805	1,805	315	1,490

*Controls in Table 2 included. Errors clustered by hospital and year. Table B2 in the Appendix shows the results were robust when we de-aggregated the other EMR systems control variable. *** p<0.001, ** p<0.01, * p<0.05*

3.5.3 The Role of the Audit Recovery Program in Combating Upcoding

To test whether the Recovery Audit Program moderates the relationship between CPOE and upcoding, we interacted the adoption of CPOE systems with the presence of the Recovery Audit Program in the state in which the hospital is located. We found that, on average, the presence of the Recovery Audit Program weakens the effect of CPOE on CMI, and the coefficient represents approximately a reduction in payments of about $400 million when the audit program is implemented. On average, the relationship between CPOE and CMI becomes statistically insignificant when a hospital is covered by the Recovery Audit Program.

These analyses serve a dual purpose; first, they provide evidence that Recovery Audit Program can combat upcoding (in line with H3). Second, we are able to use the results of the Recovery Audit Program to rule out alternative explanations that could be driving our main results. If CPOE systems were in fact leading to more complex patients being attracted to the hospital or a more accurate coding, the program would *not* moderate the relationship between CPOE systems and CMI. However, we found that that the introduction of the Recovery Audit Program attenuates the relationship between CPOE and CMI, thereby providing evidence that changes in the patient profile or more accurate coding do *not* drive this relationship.

Table 21: Effect of CPOE on Case Mix under the Recovery Audit Program

	(1)	(2)	(3)
VARIABLES	CMI	CMI	CMI
	All Hospitals	For Profit Hospitals	Non-for-profit hospitals
CPOE	0.0085**	0.0160	0.0072*
	(0.0028)	(0.0124)	(0.0028)
Audit * CPOE	-0.0069*	0.0058	-0.0088**
	(0.0031)	(0.0131)	(0.0033)
Audit	-0.0069	0.0016	-0.0094*
	(0.0043)	(0.0096)	(0.0047)
Hospital and Time FE	Yes	Yes	Yes
Controls (Including presence of other EMR systems)	Yes	Yes	Yes
Constant	10.9086	0.2938	19.8147
	(12.7616)	(38.9135)	(13.9664)
Observations	14,440	2,520	11,920
R-squared	0.2901	0.3022	0.2936
Number of hospitals	1,805	315	1,490

*Controls in Table 2 included. Errors clustered by hospital and year. Table B2 in the Appendix shows the results were robust when we de-aggregated the other EMR systems control variable. *** p<0.001, ** p<0.01, * p<0.05.*

3.5.3.1 Ability of Auditors to Identify Copied Information

Certain auditors have acquired the capability to identify copied-and-pasted patient record information and over-documentation (that is, the use of default templates provided by CPOE systems). This capability allows the auditor to target the mechanisms that have been suggested in Section 3.1 to identify upcoding. To obtain information on which auditors had developed these capabilities, we filed a Freedom of Information Act information request, and we examined whether there was a greater reduction in the CMI of a hospital if the auditor had the capability to identify copied and over-documented records (Table 6). Column 1 divides the sample into three groups. The first group of hospital-years are not covered by the Recovery Audit Program. The second group of hospital-years are covered by the Recovery Audit Program, but *not* by auditors who had the capability in that year to identify copied information. The third group of hospital-years is of hospitals that are covered by auditors who had developed those capabilities. Column 2 analyzes a subset of hospital years covered by the Recovery Audit Program. We found that within this subset, hospitals that use CPOE and are covered by auditors who are able to identify copied-and-pasted over-documented records have a negative and significant effect on the CMI versus hospitals covered by other auditors without these capabilities. This implies that auditors who developed these capabilities were able to identify upcoding, whereas auditors without these capabilities were *not* able to identify upcoding.

Table 22: Effect of CPOE on Case Mix when Hospital is in area with an Auditor with the Ability to Identify Copied Information

	(1)	(2)
VARIABLES	CMI	CMI
	All Hospitals	Hospitals Under Audit Program
CPOE	0.0080**	0.0075
	(0.0027)	(0.0043)
CPOE * Audit but no copy identification	-0.0063	
	(0.0040)	
CPOE * Audit with copy identification	-0.0089*	
	(0.0039)	
CPOE *Copy Identification		-0.0123*
		(0.0058)
Copy Identification		-0.0263
		(0.0167)
Constant	16.8001	149.9640***
	(12.8744)	(33.2818)
Observations	14,440	5,698
R-squared	0.2922	0.3038
Number of Hospitals	1,805	1,805

*Controls in Table 2 included. Errors clustered by hospital and year. *** p<0.001, ** p<0.01, * p<0.05*

3.5.4 Robustness Tests

We tested the robustness of our results by: (1) the Spillover Model to examine changes in neighboring hospitals when a hospital adopts CPOE system, (2) an Instrumental Variable model to examine other factors that could be driving the effects, (3) a relative time model that tests pre- and post-treatment effects, and (4) propensity score matching to address potential endogeneity concerns, as we elaborate in detail below.

3.5.4.1 Spillover Model to Identify Changes in Patient Profile

We performed a spillover analysis to test if hospitals attract sicker patients after CPOE adoption (besides the Recovery Audit Program test). If a hospital receives more complex patients after adopting CPOE systems, the complexity of patients in neighboring hospitals should decrease because hospitals in the same area compete for the same pool of patients. We grouped hospitals based on the hospital markets defined as Hospital Referral Regions (HRR) and the Hospital Service Areas (HSA) published by the

Dartmouth atlas of healthcare (Wennberg et al. 1999). These regions are defined using Medicare data on patient movement among physicians and hospitals in national, regional, and local markets. The atlas defines two geographical areas for health care markets. The HRR is an area where there is a major referral center and people travel for referrals. Each HRR has at least one city where both major cardiovascular and neurosurgery procedures are performed. HSA is a geographical area where residents usually receive most of their health services. We use these HRR and HSA definitions to examine if the adoption of CPOE systems in a hospital is associated with a decrease in the case mix of other hospitals in a given HSR/HSA.

$$CMI_{(h-i)t} = \beta_0 + \beta_1 CPOE_{it} + \beta_2 Z_{it} + \beta_3 Z_{(h-i)t} + \beta_4 \vartheta_{it} + \beta_5 \delta_i + \beta_6 \gamma_t + \varepsilon_{it} \; [2]$$

where i stands for hospital and t stands for year and $CMI_{(h-i)t}$ represents the average CMI hospitals in HRR or HSA h at year t except for focal hospital i.

The effect of the adoption of CPOE systems on patient complexity reported by other hospitals in the hospital market is presented in Table 7. Column 1 presents the effect of the adoption of CPOE by the focal hospital on the average CMI of other hospitals in the same HRR. The results indicate that the adoption of CPOE is not associated with a significant decrease in the case mix of neighboring hospitals. In Column 2, the CMI of neighboring hospitals in the HRR is weighed by the size of the hospital measured by the number of beds in the hospital. We included the weighted average of EMR systems of other hospitals in the HRR or HSA in the empirical specification. We found that the adoption of CPOE systems by a hospital does *not* reduce the complexity of cases in neighboring hospitals. Instead, we found that the adoption of CPOE by the neighboring hospitals increases their own case mix, confirming our main results.

Panel A: Hospital Referral Regions (HRR)	(1)	(2)
VARIABLES	CMI of other Hospitals in HRR	Weighted CMI of other Hospitals in HRR
CPOE	0.0012	-0.0009
	(0.0010)	(0.0014)
Adoption of CPOE by other hospitals in the HRR	0.0173***	
	(0.0026)	
Adoption of CPOE by other hospitals in the HRR (weighted)		0.0109***
		(0.0029)
Hospital and Time FE and Controls	Yes	Yes
Controls	Yes	Yes
Constant	23.9461***	23.9461***
	(6.3666)	(6.3666)
Observations	14,112	14,112
R-squared	0.6553	0.5776
Number of Hospitals	1,764	1,764
Panel B: Health Service Area (HSA)	(3)	(4)
VARIABLES	CMI of other Hospitals in HSA	Weighted CMI of other Hospitals in HSA
CPOE	-0.0018	0.0026
	(0.0024)	(0.0052)
Adoption of CPOE by other hospitals in the HSA	0.0221***	
	(0.0059)	
Adoption of CPOE by other hospitals in the HSA (weighted)		0.0172
		(0.0141)
Hospital and Time FE	Yes	Yes
Controls	Yes	Yes
Constant	33.2714*	43.1391
	(13.3105)	(26.4942)
Observations	5,672	5,672
R-squared	0.5161	0.6115
Number of Hospitals	709	709

*Controls in Table 2 included. Additional controls include the adoption of CDR, CDSS, OE and PD, the average of discharges, number of bed admit days and number of employees for other hospitals in the hospital market as the case may be. Errors clustered by hospital and year. *** p<0.001, ** p<0.01, * p<0.05*

Table 23: Effect of CPOE adoption on Transfer Adjusted Case Mix of Neighboring Hospitals

3.5.4.2 Instrumental Variable Approach

Since EMR systems are not exogenously determined and the adoption of these systems is not randomly assigned, there could be other unobserved factors that may confound the adoption of CPOE systems as well as the corresponding increase in the case mix. To address this endogeneity issue, we used two types of Instrumental Variable (IV) analyses. The first approach was to use a Latent Instrumental Variable (LIV)

(Ebbes et al. 2005) that uses a discrete latent instrument that partitions the possibly endogenous predictor variable into two parts – one of them that is uncorrelated with the error and the other part that is correlated with the error (Zhang et al. 2009). The advantage of this method is to empirically find an instrument based on the data and not make the traditional assumptions of the IV analyses. Second, we used two instruments based on the traditional IV method. Angst et al. (2010) found that the adoption of EMR systems in hospitals is affected by its co-located peers. We built on this previous finding and argue that while the adoption of CPOE systems in a hospital may be driven in part by its peers, there is little justification to suggest that a hospital's co-located peers would have an impact on the reporting of the patients' complexity by a hospital. Hence, we used the adoption of CPOE systems in other hospitals in the hospital market as defined by the HRR (Hospital Referral Region) as an instrument for the adoption of CPOE systems in the focal hospital. Our other instrument is the number of broadband providers in the county in which the hospital is located. We argue that the ease of access to high speed Internet in the county will facilitate the adoption of EMR systems in the focal hospital. However, the presence of high-speed Internet should not directly affect changes in the upcoding behavior. In sum, for these three IV approaches, we estimate Equation (3) and (4).

$$y_1 = \beta_0 + \beta_1 y_2 + u_1 \quad [3]$$

$$y_2 = \pi_0 + \pi_1 z_1 + v \qquad [4]$$

β_1 represents the effect of the possibly endogenous repressor on y_1. y_2 is decomposed into parts in the LIV approach and regressed on z_1 in the second approach.

Table 8 shows the results for the IV analyses. We found that the positive effect of CPOE on the hospital case mix is robust to the specifications when we instrumented for the presence of CPOE systems in hospitals using all three IV approaches.

	(1)		(2)	(3)
	Peer adoption as Instrumental Variable		Number of businesses having broadband as Instrumental Variable	Latent Instrumental Variable
First Stage Regression				
	CPOE		CPOE	-
CPOE adoption by other hospitals	.3706***	Number of Broadband Providers	.0097***	-
	(.0177)		(.0019)	-
Constant	.0158	Constant	.0064***	-
	(.0144)		(.0224)	-
Number of hospitals	1,764	Number of hospitals	1,617	-
Number of observations	14,112	Number of observations	1,617	-
Second Stage Regression				
	CMI		CMI	CMI
CPOE	.0367**	CPOE	2.0851***	.0998***
	(.0128)		(.4280)	(.0243)
Constant	1.3593***	Constant	1.1259***	-5.042***
	(.0094)		(.0507)	(.8439)
Number of hospitals	1,764	Number of hospitals	1,617	
Number of observations	14,112	Number of observations	1,617	11,568

*Conventional standard errors in parenthesis. *** p<0.001, ** p<0.01, * p<0.05*

Table 24: Results of the Instrumental Variable (IV) Model

Table 25: Effect of the Adoption of CDR on the Hospital Case Mix

	(1)	(2)
VARIABLES	CMI	CMI
PD	-0.0006	-0.0007
	(0.0016)	(0.0016)
CDR	0.0030	0.0017
	(0.0020)	(0.0019)
CDSS	-0.0015	-0.0012
	(0.0017)	(0.0017)
OE	-0.0025	-0.0042
	(0.0027)	(0.0027)
Constant	1.3714***	11.1081
	(0.0027)	(12.7579)
Hospital and Time FE	Yes	Yes
Controls	No	No
Presence of other EMR systems	Yes	Yes
Observations	14,440	14,440
R-squared	0.2609	0.2898
Number of Hospitals	1,805	1,805

*Socio-Demographic control included. Errors clustered by hospital and year *** p<0.001, ** p<0.01, * p<0.05*

3.5.4.3 Physician Documentation and Upcoding

We also tested the relationship between Physician Documentation (PD) and CMI as a falsification test. If there is a spurious relationship between CPOE and CMI due to unobserved covariates, we would expect to find a similar relationship for the PD system, which is another advanced EMR system that is similarly complex to implement and use (and thus related with the unobserved covariate). We found that the presence of the PD system does not have any statistically significant effect on the case mix of the hospital. Additionally, other systems (CDR and CDSS), while classified as basic, also do not show any statistically significant effect of their use on the complexity of patients that hospitals report, supporting our findings.

3.5.4.4 Relative Time Model

In previous models, we used hospital and year fixed effects to control for time invariant unobservable heterogeneity across hospitals and time specific shocks that are experienced by all hospitals. In this set of analyses, we analyze the *temporal directionality* of the relationship between CPOE adoption and case mix. This would address questions whether the CPOE systems adopted by hospitals that already have a high case mix, and how long it takes for a statistically significant increase in the case mix to materialize after adoption of CPOE systems. To do this, we utilized a relative time model (Greenwood et al. 2015),

$$y_{jt} = \rho'[s_2 * \varphi] + M'\theta_2 + X'\delta_2 + G'\gamma_2 + v + \varepsilon \ [5]$$

where y_{jt} is the CMI of the hospital j in year t, s_2 is a binary variable indicating if the hospital j adopts CPOE sytsems, φ is a set of time binary variables indicating the number of years between the year of the observation and the adoption of CPOE systems in hospital j. We further included hospital fixed effects (M), time fixed effects (X), hospital and county level controls (G) and a constant (v).

We further interacted the relative time with the presence of audit in that year. Table 10 presents the results. In Model 1, we found that whereas there is no statistically significant difference in the pre-treatment effects, there is a statistically significant post-treatment effect, 2-3 years after the adoption of CPOE systems. We also found that the magnitude of the coefficient increasing after the adoption of CPOE systems.

After interacting with the presence of the Recovery Audit Program, we found evidence of the effect being moderated two years after the adoption of CPOE systems (in the presence of the Recovery Audit Program), although outside the Recovery Audit Program, there is an increase in the case mix that the hospital reports.

Table 26: Relative Time Model

	(1)	(2)
VARIABLES	CMI	CMI
CPOE (t-4) * Audit		-0.0032
		(0.0068)
CPOE (t-3) * Audit		0.0067
		(0.0060)
CPOE (t-2) * Audit		-0.0029
		(0.0059)
CPOE (t-1) * Audit		-0.0042
		(0.0050)
CPOE (t) * Audit	Omitted	
CPOE (t+1) * Audit		0.0011
		(0.0059)
CPOE (t+2) * Audit		-0.0193***
		(0.0065)
CPOE (t+3) * Audit		-0.0039
		(0.0084)
CPOE (t+4) * Audit		-0.0055
		(0.0123)
CPOE (t-4)	-0.0028	-0.0024
	(0.0028)	(0.0031)
CPOE (t-3)	-0.0026	-0.0039
	(0.0026)	(0.0029)
CPOE (t-2)	-0.0025	-0.0016
	(0.0027)	(0.0030)
CPOE (t-1)	0.0007	0.0028
	(0.0027)	(0.0034)
CPOE (t)	Omitted	
CPOE (t+1)	0.0033	0.0027
	(0.0032)	(0.0043)
CPOE (t+2)	0.0041	0.0155***
	(0.0035)	(0.0049)
CPOE (t+3)	0.0125***	0.0154**
	(0.0045)	(0.0065)
CPOE (t+4)	0.0121**	0.0169
	(0.0054)	(0.0112)
Audit		-0.0058
		(0.0043)
Observations	14,440	14,440
R-squared	0.2903	0.2911
Number of Hospitals	1,805	1,805

*Controls in Table 2 included. Errors clustered by hospital and year *** p<0.001, ** p<0.01, * p<0.05*

3.5.4.5 5.4.6 Propensity Score Matching

Finally, we created a matched sample between hospitals that adopt and hospitals that do not adopt CPOE systems using propensity score matching (PSM) method. This approach matches a group of hospitals that adopted CPOE systems with another group of hospitals that are similar to the size and type of the hospital (by following the previous literature (Adler-Milstein et al. 2014), but did not adopt CPOE systems. The matched sample was balanced in terms of size and hospital type with no statistically significant differences across the treated and untreated samples. Table 11 shows the results of the impact of CPOE adoption on CMI based on PSM where our main results remain robust to this alternative specification.

Table 27: Propensity Score Matching

	Matched on Type of hospital and Size	Matched on Type of hospital, size and location of Hospital (HRR codes)	Matched on Type of hospital and Size
Average Treatment Effect of Treated	.065***	.047***	.0351***
	(.015)	(.018)	(.0145)
Number of Observations	1805	1783	10,698

*Analysis for Columns 1 and 2 done for data in year 2007. Column 3 restricts analysis to years before 2010 to control for effects of audit. *** p<0.001, ** p<0.01, * p<0.05*

3.6 Discussion

3.6.1 Key Findings

EMR systems offer multiple benefits for hospitals, patients, and society in general (Buntin et al. 2011; Chaudhry et al. 2006). EMR adoption has several important positive consequences, such as a reduction in infant mortality (Miller et al. 2011) and lower hospital error rates (Bates et al. 1999). Therefore, the adoption of EMR systems has been encouraged by the government as a mechanism to reduce healthcare costs and improve patient care. Although EMR systems can facilitate better record keeping for hospitals, the same systems also enable hospitals to manipulate their patient records to artificially reap higher profits. We show evidence that hospitals may be using EMR systems inappropriately since the adoption of CPOE systems may be facilitating physicians to "upcode" for healthcare services in a potentially unethical manner – a practice that has attracted the interest of regulators, the higher levels of government, and also the public.

Overall, we found evidence that the adoption of CPOE systems leads to an increase in the case mix index of hospitals, and that this effect is stronger among for-profit hospitals and for those hospitals that are co-located with other for-profit hospitals, consistent with the inappropriate practice of "upcoding" after the adoption of CPOE systems. On average, we find that the direct effect of the adoption of CPOE systems is hospitals reporting an increase of .35% in their case mix. However, this effect is moderated by the type of hospital and the presence of a Recovery Audit Program. Our results were robust several specifications and tests. Table 12 summarizes the economic effects of our empirical results.

Table 28: Economic Effects of CPOE Adoption across Hospitals

	All Hospitals	For Profit Hospitals	Not for profit hospitals
Change in TACMI	0.005	0.020	0.004
Average case mix in 2010	1.45	1.369	1.475
% Effect	0.35%	1.46%	0.27%
Additional Payments	$302,139,505	$116,445,306	$185,694,199
Number of Hospitals	1805	315	1200
Per Hospital Additional Re-imbursement	$167,390	$369,667	$154,745

3.6.2 Implications for Theory

There are several theoretical implications that can be derived from our study's findings:

3.6.2.1 Implications for the Emerging Literature on "Upcoding"

We contribute to the emerging literature on the effects of EMR systems on upcoding. Our results provide a mechanism for addressing the conflicting results in the literature studies (Adler-Milstein et al. 2014; Li 2014). Breaking down the three hypotheses we examine – we found a statistically significant role of the adoption of EMR systems in upcoding (H1). Second, we found that for-profit hospitals are more likely to show a higher level of case mix after they adopt CPOE systems (H2) – a finding that is in line with the proposed logic of upcoding, but for which there exists limited empirical justification in the literature. Third, we use the Recovery Audit Program as a quasi-natural experiment to empirically support our theorization (H3), and show that there are ways to combat the presence of upcoding.

Our results provide a plausible empirical explanation for the mixed results of the various previous studies (Adler-Milstein et al. 2014; Li 2014). We find evidence that on average there is a direct impact of the adoption of CPOE systems on hospitals reporting an inflated case mix– but that factors such as the type of hospital and the audit program may moderate the impact. While in this paper we just examine a few factors, there are other variables that may moderate the relationship between the adoption of CPOE systems and the case mix that hospitals report. Identifying and studying these factors would allow us to inform policy on methods that can be used to attenuate the inappropriate use of Electronic Medical Record systems.

3.6.2.2 Implications for Default Options Theory

In this paper, we argue that upcoding is facilitated by the default inclusion of information in to a patient's medical record. The theory of default effect argues that when an option is provided as default, it increases the likelihood of being selected. This theory has been used to understand strategies in marketing (for setting defaults of the options that firms should specify if they wish to have their customers make certain types of decisions) as well as in healthcare research (to provide certain types of procedures as defaults to limit the risk of infection) and to explain different rates of organ donations among countries. The default option effect has been studied in various literatures; however, this phenomenon has received limited attention by healthcare IS scholars. However, we argue that the provision of an option as the default option can influence the manner in which data are created in the first place. Setting a certain option as the default option for physicians can shape the reimbursements that are provided to the hospital as well as the statistics that are used to characterize the hospital (in our case, the case mix that the hospital reports). Our results provide evidence that data generated via default options maybe subject to cognitive biases or manipulations. As we demonstrate, the use of such data for the purposes of reimbursement may be severely biased, and those data may be inconsistent with the underlying process. Therefore, users of data (hospitals and researchers) need to use data generated based on the default options with caution and possibly identify and treat such data to remove any inherent biases that may exist.

3.6.2.3 Implications for EMR systems and the Structure of Hospitals

Harris (1977) argued that hospitals are organizations that have two different structures – an administrative side and a clinical side. The administrative side is responsible for the financial solvency of the hospital, and the clinical side is responsible for treating patients. Although the use of CPOE systems is primarily intended as a mechanism for physicians to record better patient information to improve patient care and reduce medical errors, an increase in the case mix increases the reimbursement to the hospital and helps the administrative side of the hospital more than its clinical side. If upcoding is indeed taking place (as our results suggests that it does), the recording of clinical data, which was traditionally the role of the clinical side of the hospital is being co-opted by the administrative side (by the setting of defaults in these systems) to further achieve its goals (Barley 1986). The effects of CPOE adoption on the hospital case mix are stronger among for-profit hospitals where there is less demarcation between the objectives of the administrative and the clinical side of the hospital. As these organizations often allow physicians to own equity in the hospital (to align the incentives of the clinical side with the financial incentives of the administrative side of hospital), it can be argued that there is less demarcation between the clinical side and the administrative side of these for-profit hospitals. And our results indicate that in for-profit hospitals, the clinical side is being co-opted to a greater degree than in not for-profit hospitals.

3.6.2.4 Broader Impacts of our Understanding of Information Systems

Interestingly, while information systems (EMR in our study) increase the ability of hospitals to upcode, auditors also use information systems to identify upcoding in patient records. These results provide a tradeoff between the means by which information systems can be used both ethically to affect the cost and quality of healthcare and also unethically to artificially increase the societal cost of healthcare. Ultimately, the appropriate or inappropriate use of EMR systems in hospitals and its impact on healthcare costs will depend on how hospitals, physicians, and auditors use these systems and the programs and policies that are put in place by policy makers to promote the ethical use of these systems in hospitals.

A nascent stream of research has also identified the fact that the agent that is in charge of setting the default option may also have its own objectives (Altmann et al. 2013). In this paper, we contribute to this stream of research, and we find that the when there is an alignment of objectives between the decision maker (e.g., the clinical side of the hospital) and the default setter (e.g., the administrative side of the hospital), there will be a higher degree of the default option being selected. However, oversight programs (such as the audit program) can moderate the use of the default option. Hence, researchers need to be aware of agency issues between the default setter and default user.

3.6.3 Implications for Practice and Public Policy

We found that the adoption of CPOE systems is associated with .35% increase in the reported case mix of a hospital. Also, we found for-profit hospitals to be more likely to upcode their patients (in line with H2), and we found that the adoption of CPOE systems by for-profit hospitals increases their case mix by 1.3% (Table 9). In terms of economic effects, by using a hospital specific rate of $8,978.39 with the number of Medicare discharges, the increase in reimbursement per patient would increase by $46.6 after the adoption of CPOE systems.[15] The total number of 'bills' of Medicare in 6,654,225 across all hospitals in our sample in 2010, this would represent an additional payment of over $300,000,000. This translates into additional payments of an average of $167,390 per hospital, which differs from $154,745 per not-for-profit hospital to $369,667 per for-profit hospital. Although these figures may be modest compared to the $136.1 billion paid out by Medicare in 2010 (representing a small percentage of the total Medicare budget), they are nevertheless significant amounts in the overall fight to reduce healthcare costs and reduce taxpayer dollars.

Finally, we found that the Recovery Audit Program has been able to promote the use of CPOE systems to report the true case mix of hospitals. We found that hospitals that are not covered by the audit program show statistical increases in the case mix that they report after the adoption of EMR systems; this effect was attenuated as the Recovery Audit Program was rolled out. Additionally, auditor capabilities to identify the use of templates and copied information were able to effectively attenuate the effect of EMR systems on upcoding. Although hospitals have argued that there are significant delays in resolving disputes between them and auditors (United States Senate Committee on Finance 2015), the audit program should be strengthened as it has the ability to moderate the use of CPOE systems to upcode. Additionally, all auditors across the country should be trained to develop the capability to identify the use of templates and copied information from electronic medical records.

3.6.4 Limitations

There are limitations and inevitable alternative explanations that we cannot perfectly rule out.

First, our research utilizes aggregate case mix data of hospitals across the US. We chose to this aggregate data over examining patient level data for two reasons. First, a nationwide analysis allows us to model trends across the all the states in the US. As Medicare reimburses all states, we analyzed country-

[15] The hospital specific rate is determined by the multiplying the average payment amounts for all DRGs with the number of patients in these DRGs. These values are then added to give the total Medicare payment for the hospital and divided by the number of cases in the hospital to give the hospital specific rate for the hospital. An average of these values for 2010 gives $8,978. If number of cases had been suppressed, then we replaced the value with 0.

level data. Patient level data is often only available for a subset of states (or for a sample of patients) and hence we would have been limited in the generalizability of our results. Second, by using aggregate data from across the US, we were able to leverage the staggered roll-out of the Recovery Audit Program as a moderating factor. If our analysis were to be limited to just a few states, we would not have been able to comprehensively utilize the audit program as a quasi-natural experiment. However, while we have used the audit program to rule out if CPOE systems are capturing more information, patient level data may allow us to further examine what kinds of DRGs are showing more and less coding and allow us to draw inferences about the increase in case mix that we observe.

Second, our research has been limited to patients that belong to the Medicare pool. Medicare insures 48 million Americans with reimbursements of $183 billion in aggregate hospital stays for 15.3 million hospital stays in 2011, accounting for about half of the nation's total medical care costs (Torio et al. 2013). These astronomical amounts have raised concern about the continued viability of Medicare Part A (funds that are used to pay for medical services including in-patient hospitals) (Centers for Medicare & Medicaid Services 2015a). As taxpayer dollars pay for Medicare, it is important to determine if tax dollars are being used to pay for unethical hospital practices. The effect of the adoption of CPOE systems may not be limited to changes in the case mix of hospitals, and the adoption of CPOE systems may also increase the complexity of cases that are reported to private insurers. However, we opt to limit our analysis to Medicare since it is the single largest insurance provider, and it is funded by taxpayers' dollars.

Third, we are unable to determine if CPOE systems are adopted with the strategic objective of the hospital to increase its case mix with upcoding, or if the increase in the case mix happens naturally without any prior strategic intent. However, this question is outside the scope of our study since we are specifically interested in determining if the practice of upcoding takes place, or not, rather than strategic objective that drove the decision of the hospital when the system was adopted.

Finally, while the financial figure that we attribute due to the occurrence of upcoding may not seem massive when compared to the colossal Medicare budget, it should be remembered that the $302M in artificial overpayments due to upcoding comes from public money that is funded by taxpayers' dollars.

3.6.5 Concluding Remark

As President Obama took office in 2009, he made the use of Information Technology central to the fight to reduce the rapidly growing healthcare cost. In his inaugural address, he stated, "We'll … wield technology's wonders to raise health care's quality and lower its cost" (Obama 2009). Since then, researchers (Dranove et al. 2012) have attempted to shed light on the "trillion-dollar conundrum": Will the adoption of EMR systems reduce the rapidly escalating costs of healthcare provision?

While there is consensus that the adoption of EMR systems can fundamentally change the manner in which healthcare services are provided in the US, there is a heated debate on whether these changes will be for the better or the worse. CPOE systems, in particular, have been found to have beneficial effects on healthcare quality with studies showing that these systems can reduce the number of errors in hospitals; these benefits do not need to come at the cost of inflated Medicare reimbursements using taxpayers' dollars. Our results indicate that EMR systems could be used in a potentially inappropriate manner to inflate Medicare reimbursements, but at the same time indicate that there are information systems that can be used to attenuate this unethical practice. Overall, incentives and disincentives that are in place can influence the manner in which EMR systems are used which can provide a solution to this "trillion-dollar conundrum."

CHAPTER 4 : ANTECEDENTS AND CONSEQUENCES OF ELECTRONIC MEDICAL RECORD SYSTEM ABANDONMENT

4.1 Introduction

The adoption of Health IT is promoted by the US government as a mechanism to reduce the high costs of health care. Towards this objective, the US government provided $34 billion in the 2009 Health Information Technology for Economic and Clinical Health Act (HITECH Act). The act provides financial incentives for hospitals to adopt Electronic Medical Record (EMR) systems as well as imposing penalties on hospitals that do not comply.

The benefits of investing in Health IT is currently being debated (Chaudhry et al. 2006; Sidorov 2006). Studies have argued that the adoption of EMR systems is associated with an increase in the adherence to guideline-based care (Overhage et al. 1997), fewer medical errors (Chertow et al. 2001), reduction in the utilization of care (Tierney et al. 1990), as well as a reduction of operating costs in neighboring hospitals (Atasoy et al. 2014). However, installation cost of these systems is extremely high with costs ranging between $3 million for a 250-bed hospital to $7.9 million for a 500-bed hospital (CBO 2008). Additionally, like other IT systems, the adoption of health IT systems takes much more than just plugging in a computer. The adoption of these systems requires modification to a number of different processes and tasks to support the deployment of the new infrastructure (Bresnahan et al. 2002; Soh et al. 2004).

Additionally, investment in advanced Health IT systems often involves coordinating a number of different IT systems across different hospital divisions. The adoption of these systems changes workflows and work definitions which is met with resistance from. Due to the strict requirements of EMR systems that ensure that physicians enter the name of the drug that they wish to prescribe correctly, physicians have found the usage of some of these systems to be problematic (Bowman 2013). In addition, the public failure of the adoption of EMR systems at Cedar-Sinai hospital in Los Angeles, CA–illustrated the resistance of users to hospital-wide EMR systems (Connolly 2005).

In this study we seek to understand issues surrounding the abandonment of EMR systems. We classify the different types of abandonment that hospitals may experience of their EMR systems and examine which systems are more likely to suffer from which types of abandonment. Additionally, the HITECH Act mandated the adoption and use of Electronic Medical Record systems by hospitals in order for them to continue to receive their full reimbursements and we use the implementation of the act as a quasi-natural experiment to examine how behavior of hospitals with regard to their information systems changes after its implementation.

This paper proceeds as follows: In the section 2, we outline previous research that has examined the impact of the abandonment of information systems in firms and of EMR systems in hospitals. In section 3, we outline the factors that we wish to study in this paper. In section 4, we discuss the data set that we will be using for our analysis, our empirical specification and the results that we find. In section 5, we discuss our findings and outline the limitations of our research.

4.2 Literature Review and Theory Development

4.2.1 Electronic Medical Records

There has been a large body of research that has examined the effect of the adoption of EMR systems on a number of different metrics (e.g. Chaudhry et al. 2006; Dranove et al. 2012; Miller et al. 2011). These studies have broadly examined the effect of 5 different EMR systems that form the basis of our study:

- Clinical Data Repository (CDR): CDR is a database for storing current and historical patient data. Details about the patient medications, test results, procedures that were conducted and even demographic information can be stored in the data repository. A study at the Beth Israel Deaconess Medical Center found the adoption of the CDR system leads to hospital infection control (Samore et al. 1997).

- Clinical Decision Support System (CDSS): CDSS is a tool that physicians use to diagnose patients and their health conditions. The system works by taking patient level data and using algorithms to generate recommendations. The system has been used for a number of types of suggestions particularly in the case of chest pain, treatment of infertility and the timely administration of immunizations (Garg et al. 2005). Studies have found that the adoption of the system leads to improvements in the cardiovascular disease management (Barnett et al. 1983), management of urinary incontinence (Petrucci et al. 1991) and benefits in computer assisted anticoagulant dosing (White et al. 1987).
- Order Entry (OE): This is a legacy system that allows for multiple different sites (such as a nursing station, service areas and other ancillary departments) to enter data to produce composite results for the patient. A billing function is often a by-product of the use of this system.
- Computerized Physician Order Entry (CPOE): The CPOE system contains information about the specific needs of the patient that can be useful in reducing prescription and medical errors. The CPOE system allows physicians to coordinate delivery of medicines, order laboratory and radiology studies as well as transfer information between different care providers. The system is often connected up with the CDSS system to identify mistakes that may have occurred and to check for various drug interactions.
- The PD system keeps an electronic database of past patient conditions that have been reported to the doctor and can help with better diagnoses. The system works by automating the workflow, enabling input of structured data and allowing for communication between different stakeholders in the hospital.

In the literature, these technologies have been categorized as basic versus advanced IT technologies (Agha 2014; Dranove et al. 2012; HIMSS 2011). Basic IT technologies consist of Clinical Data Repository (CDR), the Decision Support System (CDSS), and Order Entry (OE) system. Advanced IT systems include the Computerized Physician Order Entry (CPOE) system and the Physician Documentation (PD) system with advanced systems being more difficult to implement and require the coordination between a number of different departments.

4.2.2 Evolution of Information Systems

Numerous studies have examined the phenomenon of the adoption of technologies by firms (Thong 1999). However, software that is adopted is often not static and continuous updates are made to the software over time as it evolves (Lehman 1978; Lehman et al. 1985). Additionally, the requirements for an organization on their information system may also change and legacy systems (or its updates) will be unable to fulfill the needs of the organization. Instead, the organization may feel that another information system has a better fit for the organization.

Hence, rather than continuously update the system that the organization is based on, the organization may instead choose to fundamentally switch the system that it uses. Such a switch would involve a radical shift to a different system which would change the how users use the system and may bring switching costs to the newer system. However, the organization may feel that it is prudent to move to another system due to the better fit that the new system has.

4.2.3 Abandonment of EMR systems

Abandonment has been described as either a temporary or a permanent retirement of a project that is currently under operation (Ewusi-Mensah et al. 1991; Greenwood et al. 2016). The issue of abandonment has received considerable attention in the realm of IS projects with a number of studies documenting that the substantial occurrence of this event. Studies have argued that 50% of IS projects fail (Lyytinen et al. 1987), only 11% of IT projects deliver their planned benefits (Kearney 1990) and another statistic puts the number of failed projects at 70% (Hochstrasser et al. 1991). Other statistics are no less alarming. Clegg et al. (1997) finds that 90% of IT projects fail to meet their goals and 80% of them are late and over budget and 40% are abandoned.

As previous research has identified failure of Information Systems, there has been an attempt to identify factors that could play a part in their successful adoption. These “critical success factors” that could potentially lead to a successful adoption of the IS system include metrics such as management support (Nah et al. 2001), coordination between different functional units (Kim et al. 2005) has an impact on if the ERP systems roll out are successful or not. However, this stream of literature has been hampered by the lack of access to large firm-level data sets. These studies have used interviews/questionnaires with managers about the experiences with ERP roll-out (Ewusi-Mensah et al. 1991), case studies to identify the factors that have an impact on the successful rollout or ERP systems as well as reviews of earlier papers examining the effect of factors on the roll out of ERP systems. Due to the limited availability of data, these studies have been unable to identify the types of organizations that would be more likely to abandon their systems or examine the impact of a policy change in abandonment rates.

Additionally, there are number of reports of the occurrence of failure of the implementation of electronic medical record systems in hospitals. Among the most famous of cases is that of Cedar-Sinai which invested $34 million towards the adoption of a component of its EMR system. The system was found to be unusable due the system not being able to recognize words that had slight spelling mistakes in them, limited the ability of physicians to make medical judgments and the requirement for the strict adherence to procedure that contributed to the problematic roll-out of the system. After a several hundred of the physicians refused to use the system, the system was eventually withdrawn (Connolly 2005). Another hospital that experienced problems implementing an EMR system was the Kaiser Health Plan system in Hawaii. In 1999, the organization initially chose to adopt the Clinical Information System (CIS) that had been jointly developed by Kaiser Permanente and IBM. However, many users perceived that the initial decision of the adoption of the system was taken without considering the local environment and hence the system limited the productivity of clinicians. Eventually, the hospital ended up halting the roll-out of the system and instead focused on adopting a system developed by Epic (Scott et al. 2005).

These are hardly isolated cases of EMR systems being abandoned in hospitals. Leviss et al. (2010) complies an anthology on case studies of problematic cases of implementation of EMR systems. With 37% of the hospitals in our study experiencing an abandonment in their IT systems, we attempt to understand the critical success factors in the implementation of EMR systems and the impact of abandonment of these systems.

In sum, while individual cases of abandonment of EMR systems have been documented a systematic analysis of the factors that identifies which organizations are more likely to abandon their information systems has not been examined. In this study, we examine the role that the size of the organizations plays along with the introduction of an act that mandates the adoption and use of systems and the impact that it would have on abandonment decisions of hospitals.

4.3 Hypotheses Development

4.3.1 Factors driving the abandonment of EMR systems

4.3.1.1 Co-ordination and Establishment of Community Standards

In 2009, the US implemented the HITECH Act. The Act provides financial incentives to hospitals to adopt and use Electronic Medical Record systems but at the same time mandates that hospitals need to demonstrate that they use EMR systems in a meaningful manner in order to continue to get Medicare reimbursements. Hospitals needed to adopt certified EMR systems that met standards that were specified by the CMS. The HITECH Act also hopes for a path to interoperability between the EMR systems of different providers in the future (CDC 2016).

We examine if community standards that were mandated in the HITECH Act would have any impact on switching behavior that was exhibited by hospitals. In addition, the HITECH Act provides external standards that need to be met by organizations. It is due to this degree of external standards that the institutional inertia that exists in organizations may be moderated and instead larger organizations would be more likely to switch the system that is being used.

H1a: The probability of abandoning a system will be lower for a hospital during the HITECH Act.

H1b: The probability of switching systems will be higher for a hospital during the HITECH Act.

4.3.1.2 Size of Hospitals

Larger organizations have been found to be more likely to have the resources to adopt innovations (Dewar et al. 1986; Moch et al. 1977; Utterback 1974). This is symptomatic of the fact that smaller organizations face barriers related to the financial resources and a lack of IT expertise (Ein-Dor et al. 1978; Ein-Dor et al. 1982). Larger firms are also associated with higher degrees of slack that allows them to take larger risks (Bourgeois 1981; Rhyne 1985). This has been extended to IT adoption and studies have argued that larger firms will be more likely to adopt IT (Thong 1999). We argue that many of the same factors (such as access to skills, financial slack and access to IT expertise) that allow larger firms to adopt innovative practices will also help with the roll-out of these innovative practices and hence allow them to switch the systems that they use. Hence we posit:

H2a: The probability of abandoning an information system will be greater for larger hospitals.

However, another stream of research has argued that larger firms are also those with greater organizational inertia (Hannan and Freeman, 1984). This inertia keeps larger organizations from changing strategies quickly to adapt to changes in their environment. This is due to larger organizations having higher co-ordination costs to implement organization-wide changes. Hence, while larger organizations may have the resources to switch systems, they may be hemmed in by constraints that exist for larger organizations.

H2b: The probability of abandoning an information system will be lower for larger hospitals.

4.3.1.3 Establishment of Standards

As organizations decide to switch the system that they use, they may adopt the same system that is in use by neighboring organizations. This decision to opt to select the same system as another organization could have a number of impacts such as making the systems more interoperable. Interoperability deals with systems in different organizations being able to share information amongst each other. While it is especially difficult in the case of Electronic Medical Record systems (due to privacy requirements and the need to establish standards to enable the sharing of information between similar systems), it is especially important in the case of healthcare management as it allows hospitals to share information amongst each other potentially reducing the duplicative and unnecessary testing.

A choice by a hospital to adopt the same system as its neighbor may also be driven by the fact that the organization now has evidence that the system that they wish to use has been shown to be effective in its peers. This successful demonstration may also motivate other organizations to adopt the same software.

While the theories behind the switching of systems and the reasons organizations may adopt the same systems has been recognized, it is not known if larger organizations are the ones that set the standard or if they adopt the community standard. As larger organizations have larger resources that are available to them, they are often the first ones to adopt risky systems. Hence, these larger organizations may not be the ones that set the standard as other organizations may be the ones that adopt a system that goes on to be the dominant one in the market. Hence, larger organizations may only later adopt the software that is in use in the market.

H3a: Larger hospitals are more likely to select the software that is the dominant one among its neighbors.

However, larger organizations may be the one that set the standard. Hence, larger organizations may use their market share to adopt a different system as opposed to the one that is the dominant one in the market. As larger organizations often do not need to integrate their systems with other smaller organizations, they may instead opt for not integrating their systems. Hence, we posit:

H3b: Larger hospitals are less likely to select the software that is the dominant one among its neighbors.

4.4 Impact of EMR Abandonment

Together there has been extensive research on the impact of the adoption of these systems on a variety of metrics with studies finding effects of the adoption of these systems on the cost and performance metrics of hospitals. Studies that have looked at the adoption of these systems on cost have found that the adoption of these systems is associated with an increase in the level of operational cost of the adopting hospital (possibly due to the training that the staff in the hospital needs to undertake) (Dranove et al. 2012). However, Atasoy et al. (2014) found that neighboring hospitals see a decrease in their own operational cost.[16]

It has widely been recognized that the adoption and the abandonment of IT is not costless. There has been a non-negative cost of the abandonment of technologies that has been extensively modeled in economic studies. This indicates that although it is widely recognized that the abandonment of systems is not costless, there has yet to be any analysis on the cost of abandonment of electronic medical systems. Although the impact of EMR adoption has been extensively studied, the consequences of the abandonment of these systems has not been differentiated from the impact of adoption. The abandonment of these systems may have disproportionate effects on outcome variables compared to the adoption of systems.

Additionally, just as the adoption of information systems is not as easy as simply plugging in a computer (Bresnahan et al. 1996), the abandonment of the systems will not be as easy as unplugging the system. The adoption of EMR technologies involves a process of changing routines and procedures and the abandonment of a system may come with its own changing of procedures. Instead, it is entirely possible that the abandonment of systems will have a long-term effect on the operation of hospitals. Hence, we posit:

H3: Under the HITECH Act, there will be positive costs to switching an information system.

[16] We restrict ourselves to an analysis of the impact of the abandonment on costs. However, the metric can be extended to neonatal mortality, adverse drug effects and other metrics.

4.5 Data

To obtain information about the abandonment of electronic medical record systems by hospitals, we use information provided by the Healthcare Information and Management Systems Society (HIMSS) database. The database contains hardware and software adoption for more than 5300 healthcare providers across the nation. The data is collected via administering a survey to different hospitals and has come to be widely used in Health IT research.

For purposes of this paper, we limited our analysis to data from years between 2006 and 2013 as prior to 2006, HIMSS did not collect data for all the system that we wish to analyze. For a particular system, say Clinical Data Repository, we define the abandonment of the system if it in use in the hospital in a particular year and then the hospital does not use it in the subsequent year.[17] We code a shift in the software as a shift in the software provider (such as a shift from Siemens to Epic for the CDR system) if the provider has two different system providers in two successive years. However, if the software provider is not reported, we do not consider it a candidate for software changes. Additionally, a hospital enters our analysis for a particular system only if it is recorded as having adopted it for a particular year (as it is meaningless for a hospital to abandon the use of a system if it never adopts it) and only when we have data for all the years for that system for that hospital (that is a balanced panel for system adoption).

After a hospital adopts an EMR system, there are 5 possible outcomes in any of the subsequent years. Table 1 lists the five different outcomes that are possible in any year after a hospital adopts a particular EMR system. Out of the 5 possibilities that we list, three are linked directly to abandonment whereas it is also possible for a hospital to switch its systems provider without abandoning the use of the system (for example, it is possible for a hospital to go from using Siemens to using Epic without any major disruption). Although

[17] We use the codes "Live and Operational" and "To be Replaced" to indicate that the hospital has the system operational.

it is technically possible for a hospital to upgrade the within the same software (say from Epic 7 to Epic 8), we do not consider this possibility in our study as the disruption that a within system upgrade is bound to cause will be limited as opposed to a switching or abandonment of the system that is in use.

Table 29: Types of Actions a Hospital after adopting an EMR system

Continue	In this scenario, a hospital continues using the EMR system without abandoning its use or switching to a different software provider.
Switch without Abandonment	In this scenario, a hospital switches the EMR system without a break in the use of the EMR system. An example of this case is when a hospital goes from using Epic to Siemens in successive years without any recorded break in usage of the system.
Abandonment with software retained	In this scenario, a hospital retains the EMR system with a recorded break in the use of the EMR system. An example of this case is when a hospital retains using Epic but with a break of at least one year in the usage of the system.
Abandonment and Switch to different software	In this scenario, a hospital switches the EMR system with a recorded break in the use of the EMR system. An example of this case is when a hospital goes from using Epic to Siemens with a break of at least one year in the usage of the system.
Complete Abandonment (without re-adoption)	In this scenario, a hospital stops using an EMR system and does not readopt the system for the duration of our panel.

Table 30: Summary Statistics

		Adopt	Abandon	Re-adoption Percentage	Length of abandonment time
System Level Statistics	CDR	3151	168 (5.3%)	127 (76%)	1.5
	CDSS	3274	271 (8.2%)	206 (76.3%)	1.6
	OE	3189	208 (6.5%)	148 (71.1%)	1.5
	CPOE	2166	579 (26.7%)	304 (52.5%)	2.7
	PD	2018	592 (29.3%)	237 (40.0%)	1.9

		Switch without Abandonment	Re-adoption with Switch	Re-adoption without Switch	Roll-back without re-adoption
System Level Statistics	CDR	895 (28%)	69(54%)	58 (46%)	41(1%)
	CDSS	1452 (44%)	140(53%)	66 (47%)	65(2%)
	OE	993 (31%)	73 (49%)	75 (51%)	60(1%)
	CPOE	204 (9%)	92 (30%)	212 (70%)	275(12%)

	PD	224 (11%)	82 (34%)	155 (66%)	355(17%)
		Mean	Std Dev	Min	Max
Hospital Level Statistics	Abandonment of One system at least	.373	0.483	0	1
	Abandonment of a basic system	.141	0.347	0	1
	Abandonment of an advanced system	.282	0.15	0	1
	Proportion NFP	.599	0.49	0	1
	Proportion Government	.1606	0.367	0	1
	Proportion for Profit	.148	0.355	0	1
	Number of Beds	165.21	154.332	4	2545
	Percentage in Urban Location	.90	0.286	0	1

Table 2 outlines the abandonment rates for the 5 systems that we consider in this paper. The majority of hospitals that abandon the use of a system go on to readopt the system. We find that the proportion of hospitals that abandon the use of an EMR system at some point ranges between 5%-29% (of the hospitals that have the system at some point) with systems with higher complexity (advanced EMR system) having a higher probability of being abandoned. Table 2 also provides descriptive statistics for hospitals that go on to re-adopt. As is clear, more than 50% of the hospitals that drop IT go on to re-adopt it with re-adoption rates being much higher for basic systems as compared to Advanced Systems. Additionally, of the hospitals that readopt, they are likely to readopt a basic system more quickly than an advanced system.

Additionally, basic systems are also more likely to have a software switch without abandonment. Between 28% and 44% of hospitals experience a shift in the software provider for basic EMR systems whereas only 9-11% of hospitals that adopt advanced EMR systems show evidence of a shift in the software provider. Additionally, we find that of the hospitals that do readopt (that is they abandon the use for a year and then go on and adopt the system in a subsequent year), they are about as likely to readopt a basic system with and without a shift in the software. However, for advanced systems, they are more likely to implement the same system again. Finally, there is about a 1-2% chance that hospitals roll-back but do not readopt basic EMR systems. However, for advanced systems this number is between 12-17%.

For hospital level operational data, we made use of the Medicare Cost Reports databases. The databases contains information reported by hospitals as part of their contractual relationship with Medicare to allow Medicare to calculate costs and rates to reimburse hospitals. The data have been used in a number of different studies that allow researchers to estimate the operational characteristics of hospitals. From this database, we obtained the number of employees in the hospital, which we use as a proxy for the size of the hospital.

Summary statistics of the incidence of abandonment indicate that for the purposes of our panel, 5.3%-8.2% of hospitals abandon the use of basic EMR systems. On the other hand, 26.7-29.3% of hospitals abandon the use of advanced EMR systems. This is perhaps systematic of the complexity of implementing advanced EMR systems. Other summary statistics corroborate this – Advanced EMR systems are less likely to be readopted (40.5 – 53.3%) against 71.6-76.6% for advanced systems and for the hospitals that do readopt, the time to re-adoption is lower for basic EMR systems (which is in the range of 1.5-1.6 years) as compared to 1.9-2.7 years for more advanced EMR systems.

4.5.1 Empirical Model

While we present summary statistics to demonstrate that there are consistent patterns across all the EMR systems, we limit further analysis to abandonment and switching of the Computerized Physician Order Entry (CPOE) system. The CPOE system is one that requires a major investment in time for training physician to use the system and enter structured data so the data can be stored and analyzed in a meaningful manner. As physicians often have to make extensive use of the system to place orders and to pull up past interactions with the patient, it is a system that is often at the center of the work that is undertaken by hospitals and hence it forms our main system of interest for this analysis.

To analyze which hospitals are more likely to abandon the use of their EMR systems, we use a multinomial logistic regression to model the probability of abandonment during the duration of our panel. ϑ_i represents other characteristics of the hospital along with the characteristics of the surrounding area that we control for in our model.

The model for the ith hospital in the jth year is is as follows:

$$\boldsymbol{Abandon_{ij} = \beta_0 + \beta_1 HITECH_{ij} + \beta_2 Size_{ij} + \beta_3 Size_{ij} * HITECH_{ij} + \beta_4 \vartheta_j + \beta_4 \gamma_{ij} + \varepsilon_{ij}}$$

Where $\boldsymbol{\vartheta_j}$ are time fixed effects and $\boldsymbol{\gamma_{ij}}$ are control variables. The dependent variable abandon can take level 1 (indicating that the system was switched without abandonment), level 2(indicating that the system with abandoned and then readopted without switching the software), level 3(indicating that the system was abandoned and then the same system was readopted) or level 4(indicating that the system was abandoned and not readopted for the duration of the panel that we analyze). While there are difficulties in interpreting the interaction terms in logistic regression, we prefer to use it over a linear probability model for a number of reasons. First, the logistic model is set up to allow us to code a binary dependent variable without making any further assumptions. Additionally, the model is set up to allow us to analyze different categorical outcomes for the model such as so0ftware switching, abandonment without software switch, abandonment with software switch over the base case of the hospital not making any change in their CPOE software at that given point in time. Additionally, we interact the independent variables that we have with year dummies for the HITECH Act to assess if the act lead hospitals to make decisions in any different manner.

Additionally, we are interested in understanding the impacts of the switching of the CPOE system. Specifically, we focus on the impact on operational cost of the switching of systems (without abandoning it) after the HITECH Act is implemented. This is due to the fact that hospitals need to often switch the systems that they use after the HITECH Act to meet community standards and to maintain the levels of reimbursements that they obtain. We use the following panel model specification for the ith hospital at the jth time period of the form

$$\text{Log}(\boldsymbol{Operational\ Cost/Beds})_{ij} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Switching_{ij}} + \boldsymbol{\beta_2 Switching_{ij}} * \boldsymbol{HITECH_{ij}} + \boldsymbol{\beta_3 \gamma_i} + \boldsymbol{\varepsilon_{ij}}$$

4.6 Results

4.6.1 Factors driving abandonment

We first examine some factors that may drive the abandonment of EMR systems. Specifically we are interested in the role that size of the hospital plays and the interaction with the HITECH Act. We find that under the HITECH Act, hospitals are more likely to switch the system that they use without abandonment. Also, under the HITECH Act, hospitals are less likely to abandon the use of their systems. We also find that larger hospitals are more likely to switch the system that they have in our study period (over the base case of not doing anything). However, larger hospitals are also more likely to abandon and then readopt the systems. This could be driven by a number of factors such as larger financial resources that these hospitals may have as well as greater separation between workers and management which may lead to CPOE systems being abandoned in these hospitals.

Table 31: Probability of System Switches under HITECH Act

VARIABLES	1	2	3	4
	DV: Switch CPOE system (without abandonment)	DV: Abandon without switch	DV: Abandon and switch	DV: Abandon without Re-adoption
HITECH	0.924***	-2.008***	-2.224***	-0.651***
	(0.119)	(0.181)	(0.293)	(0.160)
Log(beds)	0.493***	0.210***	0.233**	-0.048
	(0.062)	(0.065)	(0.099)	(0.086)
Constant	-7.181***	-4.776***	-6.011***	-4.902***
	(0.331)	(0.319)	(0.498)	(0.415)
Observations	25,576	25,576	25,576	25,576

Next, we examine the effect of the interaction between the size of the hospital and the presence of the HITECH program (Figure 1). We find that during the HITECH program, larger hospitals are more likely to switch (without abandoning) the system that they use. However, outside the HITECH program, it is again the larger hospitals that are more likely to have a gap between using the system and not using the system. However, the probability of abandoning the system is extremely low during the HITECH program.

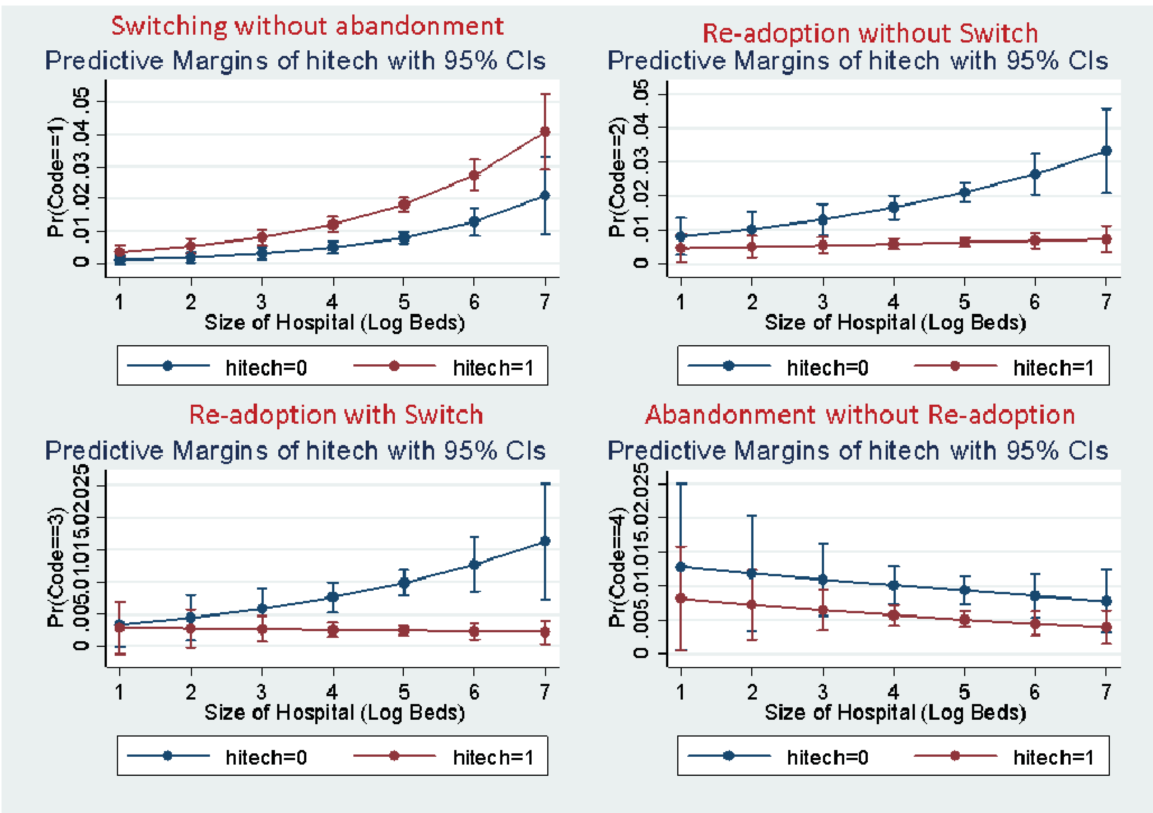
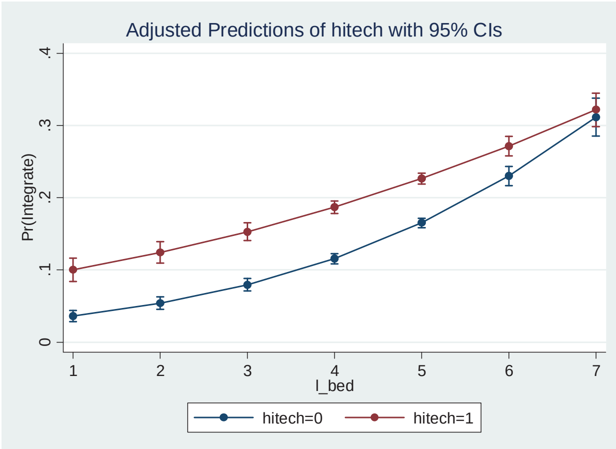


Figure 1: Effect of Interaction between size of Hospital and presence of HITECH Act

Figure 2 indicates that the probability of integration is higher under the HITECH Program. Additionally larger hospitals have a greater probability of integrating in to the established norms in the hospital market. So instead of larger hospitals leading the way, they are the ones that have the higher probability of following community norms.

Figure 2: Probability of Switching and Abandonment under different conditions



4.6.2 Impact of the abandonment of EMR systems

Next, we examine the impact of software switching that is brought about due to the switching of systems during the HITECH Act. As the act mandated a set of requirements that systems needed to meet, hospitals replaced more of their systems during the HITECH period than before. Here, we examine the impact of this switch on the standardized operational cost of the hospital. We find that switches in the CPOE system made under the HITECH program lead to an increase in the operational cost for the hospital and that these effects exist under different specifications.

Table 32: Effect of Switching the CPOE system within and outside the HITECH Program

	(1)	(2)	(3)
VARIABLES	Log(Operational Cost/Beds)	Log(Operational Cost/Beds)	Log(Operational Cost/Beds)
Switch CPOE	0.018	-0.019	-0.017
	(0.014)	(0.015)	(0.022)
Switch CPOE (t-1)		-0.013	-0.032**
		(0.014)	(0.015)
Switch CPOE (t-2)			0.005
			(0.023)

Switch CPOE * HITECH	0.015	0.044**	0.034
	(0.021)	(0.020)	(0.025)
Switch CPOE (t-1) * HITECH		0.037*	0.073***
		(0.019)	(0.019)
Switch CPOE (t-2) * HITECH			-0.003
			(0.026)
Constant	8.576***	8.627***	8.666***
	(0.002)	(0.002)	(0.003)
Observations	23,742	20,578	17,427
R-squared	0.002	0.030	0.077
Number of Hospitals	3,197	3,188	3,176

Controls include hospital and time fixed effects. We also controlled for decisions on their software the hospital may take such as the abandonment of the system (with and without re-adoption of the same or different software). Switching represents the case when the hospital changes the software that they use. Errors clustered by hospital and year.

*** p<0.01, ** p<0.05, * p<0.1

In addition, we are interested in if there are pretreatment differences in the hospitals that switch their systems under the HITECH Act. We examine this aspect by using two approaches. First, we examine if the there are systematic differences in the characteristics of the hospitals between those that adopt and those that do not using a t-test to test the difference in the characteristics between the two hospitals. Table 6 shows these results.

Table 33: Difference in Characteristics between hospitals that switch CPOE systems and hospitals that do not switch CPOE systems

	Log(Operational Cost)	Number of Beds
Hospitals switching CPOE during HITECH	18.4362	170.2
Hospitals not switching CPOE during HITECH	18.0061	184.9
T-Statistic	1.57	-0.26
p-value	0.1261	0.7980

Next, we use a relative time model to examine if there are pre-treatment differences in the operational cost for the hospitals that switch their CPOE systems under the HITECH Act. This analysis indicates that there are no systematic differences before the switch but that after the switch there is an increase in the standardized cost that is reported.

Table 34: Pre and Post effects of switching on standardized costs

	(1)
VARIABLES	Log(Operational Cost/Beds)
Switch under HITECH (t+2)	-0.039
	(0.078)
Switch under HITECH (t+1)	0.013
	(0.028)
Switch under HITECH (t-1)	0.060***
	(0.020)
Switch under HITECH (t-2)	-0.039
	(0.078)
Observations	11,209
R-squared	0.156
Number of Hospitals	3,150
Adj. R-squared	0.155

4.7 Robustness of the Results

4.7.1 Checks to see validity of abandonment data

To assess the validity of the abandonment data that we extract, we compare the rates of abandonment of EMR systems to other Health IT systems that hospitals adopt. Other systems such laboratory information systems, payroll and patient billing and are assumed to be less likely to be abandoned by the hospital. We argue that if the abandonment of EMR systems are being picked up due to coding errors, these coding errors should be as likely to show that the probability of abandoning other systems (such as payroll and laboratory information systems) should be roughly equal to the probability of abandoning EMR systems.

However, we observe that in the database, there is roughly a 1% chance of abandoning the use of payroll, laboratory information systems and patient billing in the hospitals. On the other hand, the probability of abandoning the use of EMR systems ranges between 5.3% - 8.2% for basic EMR systems and between 26.7-29.3% for more advanced EMR systems. The different in proportion between all the EMR systems compared to the payroll system was significant at 5% level of significance. We opted to compare it to the payroll system as it had the highest abandonment rate among the control systems.

Table 35: Abandonment rates for the 5 EMR systems that we consider and 3 other systems

	EMR Systems						Other Hospital IT Systems		
	CDR	CDSS	OE	CPOE	PD		Payroll	Patient Billing	Laboratory Information Systems
Hospitals Abandoning	168	271	208	579	592		51	22	48
Hospitals Using the system	3151	3274	3189	2166	2018		3273	3274	3258
Proportion	5.33%	8.20%	6.52%	26.73%	29.34%		1.56%	0.67%	1.47%

4.7.2 Robustness to Alternate Models

Additionally, we are keen to examine the robustness of our results to alternate empirical specifications. Specifically, we concentrate on examining the effect of the HITECH Program on the probability of switching a systems without abandonment. We present the results below

Table 36: Effect of HITECH on Switching

	(1)	(2)	(3)
VARIABLES	Logit	Logit Fixed Effects	LPM with fixed effects
HITECH	0.956***	0.987***	0.012***
	(0.119)	(0.120)	(0.002)
Log(beds)	0.512***	-0.440	-0.001
	(0.062)	(0.459)	(0.005)
Constant	-7.365***		0.012
	(0.332)		(0.023)
Observations	25,576	2,528	25,576
Number of Hospitals		316	3,197

4.8 Key Findings

Although the phenomenon of EMR system abandonment has been noted in case studies and covered in the popular press, there has been no systematic analysis of this phenomenon in the IS literature. This is important for a number of different reasons.

First, we find evidence for the abandonment of EMR systems in hospitals and that there may be evidence for this taking place. We describe the different ways in which systems can be abandoned by hospitals and examine which types of organizations would be more likely to abandon which kinds of hospitals.

Second, we make use of the roll-out of the HITECH Program across the United States. The program mandates the use of Information Systems and is perhaps unique in forcing all organizations in a particular sector to adopt minimum standards of Information Systems and commit to using these information systems in a meaningful manner. We find evidence that the decisions that hospitals make on how to implement their information systems changes after the introduction of the program.

Third, while larger firms have been shown to be more risk-taking, we find evidence that larger organizations are more likely to adopt the prevalent system that is in use in the community rather than selecting a different system.

Although the phenomenon of IS failure and abandonment has identified in previous research (e.g. Ewusi-Mensah et al. 1991), there has been a lack of a large scale analysis of the phenomenon. In our study, we are able to leverage a large panel of data on the adoption and abandonment of EMR systems. With a sample of more than 3000 hospitals across a panel of 7 years, we find evidence that certain hospitals are more likely to abandon systems based on their size and regulations that are in place. Additionally, we find that the abandonment of these systems increases the operational cost of hospitals and that this increase is larger than the increase in operational cost due to adoption of systems for higher lags. We hope that our analysis proves to be useful to the IS researchers who have taken tentative first steps towards identifying and understanding IS abandonment as well as healthcare researchers who seek to understand the issues surrounding the rapid adoption of EMR systems in hospitals.

4.8.1 Implications for Healthcare Management

The phenomenon of EMR abandonment has received attention in the media and among practitioners. In this study, we analyze this phenomenon and find that there are systematic differences between the hospitals that abandon the use of the system and those that do not. Smaller hospitals should be given added resources which implementing EMR systems as they are at a higher risk of abandoning the use of their EMR systems.

Additionally, we find that the impact of abandonment often results in an increase in operational cost. We find that this increases in operational cost occurs when the hospital moves to a different software or stays with the same software. However, on the other hand, if hospitals changes the software used for a system but does not abandon the use of the system, there is evidence of a reduction in the operational cost of the hospital taking place. Together this suggests that it is indeed possible for hospitals to reduce their operational cost if they seamlessly move to a new software for use in the system. However, an abrupt shift to a new software that involves a discontinuity as observed in the data results in an increase in the operational cost of the hospital.

4.8.2 Limitations and Further Research

However, there are a number of limitations to our study. Due to data limitations, we are only able to study the behavior of IT adoption for the subset of hospitals for which we have observations for all the years. Additionally, due to changes in the manner in which the data is collected by HIMSS before 2005, we only examine the panel of hospitals after 2006 which again limits the time frame for which we can examine the hospitals.

Additionally, previous research has examined a wide set of factors that influence the adoption of EMR systems by hospitals. Angst et al. (2010) finds that contagion effects are at play in the adoption of EMR systems by neighboring hospitals. Dranove et al. (2012) finds that it is the hospitals that are in IT intensive areas that are the ones that are able to achieve a cost reduction after the adoption of EMR systems. Although there are a number of different factors that we could examine that influence the abandonment of EMR systems, we limit ourselves to examining a small handful of these factors and the influence that they would have on understanding which hospitals are more like to abandon the use of Electronic Medical Record systems.

CHAPTER 5 : CONCLUSION

5.1 Contributions

The adoption of EMR systems is being justified as a mechanism to reduce the cost of providing health care services. In **Essay 1**, I find that I argue that as hospitals do not operate independent of each other, it is important to be able to assess the impact of the adoption of EMR systems on healthcare markets rather than with independent hospitals. I find that while the adoption of EMR systems leads to the increase in the operational cost of the adopting hospital, it leads to a reduction in the operational cost of neighboring hospitals. From the aspect of formulating public policy, this is an important as policy makers need to be able to account for all the changes in costs after the adoption of EMR systems. Previous research has been limited to estimating the impact that the adoption of these systems have on *own* operational cost and we find that there are cost reductions to *neighboring* hospital costs as well. Apart from the implications on public policy, and contribute to the growing IS literature that is studying the spillover effects of the adoption of Information Systems and introduce this aspect into the Healthcare economics literature.

In **Essay 2**, I find that the adoption of CPOE systems leads to an increase in the reported case mix of the hospital – evidence that hospitals may be indulging in upcoding. The upcoding of patients that has been argued to be facilitated by the adoption of the CPOE system and has been a public policy concern for the administration with former health secretary Kathleen Sebelius and the attorney general Eric Holder Jr. warning hospitals to abstain from the unethical practice. I contribute to the discussion by showing that on average, the adoption of the CPOE systems is consistent with upcoding outcomes. However, I find that the recovery audit program has the ability to reduce this outcome. Apart from the implications of my findings on public policy, I contribute to the IS literature by demonstrating an interesting method that an Information System is being used in an unintended manner.

In **Essay 3**, I examine which systems are more likely to be abandoned. I find that more advanced EMR systems (ie CPOE and PD) are more likely to be abandoned, less likely to be readopted after being abandoned and the length of time before they are readopted is also higher (Table 6) This is indicative of the more complicated implementation and maintenance of advanced EMR systems. Additionally, we find that software of advanced EMR systems are less likely to be switched without the systems being abandoned and that advanced EMR systems are more likely to be abandoned without re-adoption during the duration of our panel.

Additionally we examine the interplay between the roll-out of the HITECH program and the size of the hospitals as these two factors play a part in influencing the decisions that hospitals take about what to do with their Electronic Medical Record systems. I find that there is evidence that these hospitals are

Apart from the numerous public policy implications of the study, there are a number of implications for the IS literature. Although the phenomenon of IS abandonment has been identified in previous research to be something that affects close to 40% of hospitals, analysis of this has been limited due to small data sets. In this study, we are able to leverage a large data set to be able to study this phenomenon and identify the consequences of abandonment as well as which hospitals are more likely to abandon the use of their systems.

5.2 Concluding Remarks

The adoption of EMR systems in hospitals has changed the manner in which medical data are recorded. The adoption of these systems was motivated by the belief that the systems will reduce costs, decrease errors and unnecessary tests, enable the quick retrieval of data and allow for the better monitoring and surveillance of patient conditions. However, the adoption of Information Systems often has a number of unintended consequences. In my dissertation, I aim to explore three of these facets. I find evidence that although the adoption of these systems is motivated by improving the outcomes in the adopting hospital, it may have positive outcomes in neighboring hospitals as well. However, not all the unintended consequences of the adoption of these systems is positive. I find that one of the effects of the adoption of these systems is that hospitals may be using these systems in an unintended manner to increase the level of reimbursements. In the last essay of my dissertation, I find that the abandonment of EMR systems leads to an increase in operational cost of hospitals. I argue that this is an important outcome to study as it is important to be able to understand if the outcome is detrimental to the organization and how to avoid it.

There has already been extensive research on the direct impact of the adoption of EMR systems. However, in these essays, I examine some of the unanticipated effects of the adoption of these systems remains to be studied. I hope that my essays shed some light on this subject and spurs further research in this area.

REFERENCES

Abelson, R., Creswell, J., and Palmer, G. 2012. "Medicare Billing Rises at Hospitals With Electronic Records " Sept 21, 2012 (available at http://www.nytimes.com/2012/09/22/business/medicare-billing-rises-at-hospitals-with-electronic-records.html).

Adler-Milstein, J., and Jha, A. K. 2014. "No evidence found that hospitals are using new electronic health records to increase medicare reimbursements," *Health Affairs* (33:7), pp 1271-1277.

Agha, L. 2014. "The Effects of Health Information Technology on the Costs and Quality of Medical Care," *Journal of health economics* (34), pp 19-30.

Altmann, S., Falk, A., and Grunewald, A. 2013. "Incentives and Information as Driving Forces of Default Effects," IZA Discussion Paper No. 7610

Anderson, A., and Martin, R. 2015. "What You Should Know About Medicare Audits," in *AAOS Now*.

Angst, C. M., Agarwal, R., Sambamurthy, V., and Kelley, K. 2010. "Social contagion and information technology diffusion: the adoption of electronic medical records in US hospitals," *Management Science* (56:8), pp 1219-1241.

Atasoy, H., Chen, P.-Y., and Ganju, K. K. 2014. "The Spillover Effects of Health IT Investments on Regional Heath Care Costs," *Available at SSRN 2419690*).

Atasoy, H., Chen, P.-Y., and Ganju, K. K. 2016. "The Effect of Health IT Investments on Regional Health Care Costs," (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2419690).

Augenblick, N., and Nicholson, S. 2012. "Ballot position, choice fatigue, and voter behavior," University of California, Berkeley, Working paper.

Ballard, D. J., Ogola, G., Fleming, N. S., Stauffer, B. D., Leonard, B. M., Khetan, R., and Yancy, C. W. 2010. "Impact of a standardized heart failure order set on mortality, readmission, and quality and costs of care," *International Journal for Quality in Health Care* (22:6), pp 437-444.

Barciela, S. 1993. "Cedars, Victoria Complete Merger, Stakes to be Sold. ," 16 February.

Bardhan, I. R., and Thouin, M. F. 2013. "Health information technology and its impact on the quality and cost of healthcare delivery," *Decision Support Systems* (55:2), pp 438-449.

Barley, S. R. 1986. "Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments," *Administrative Science Quarterly* (31:1), pp 78-108.

Barnett, G. O., Winickoff, R. N., Morgan, M. M., and Zielstorff, R. D. 1983. "A Computer-Based Monitoring System for Follow-Up of Elevated Blood Pressure," *Medical care* (21:4) May 01, pp 400-409.

Bates, D. W., Leape, L. L., Cullen, D. J., Laird, N., Petersen, L. A., Teich, J. M., Burdick, E., Hickey, M., Kleefield, S., Shea, B., Vander Vliet, M., and Seger, D. L. 1998. "Effect of Computerized Physician Order Entry and a Team Intervention on Prevention of Serious Medication Errors," *JAMA* (280:15) Oct 21, pp 1311-1316.

Bates, D. W., Teich, J. M., Lee, J., Seger, D., Kuperman, G. J., M'Luf, N., Boyle, D., and Leape, L. 1999. "The impact of computerized physician order entry on medication error prevention," *Journal of the American Medical Informatics Association* (6:4), pp 313-321.

Borzekowski, R. 2009. "Measuring the cost impact of hospital information systems: 1987–1994," *Journal of Health Economics* (28:5), pp 938-949.

Bourgeois, L. J. 1981. "On the measurement of organizational slack," *Academy of Management review* (6:1), pp 29-39.

Bowman, S. 2013. "Impact of electronic health record systems on information integrity: quality and safety implications," *Perspectives in Health Information Management* (10:Fall).

Branson, B. M., Handsfield, H. H., Lampe, M. A., Janssen, R. S., Taylor, A. W., Lyss, S. B., and Clark, J. E. 2006. "Revised recommendations for HIV testing of adults, adolescents, and pregnant women in health-care settings," *MMWR Recommendations and Reports* (55:1), pp 1-17.

Bresnahan, T., Greenstein, S., Brownstone, D., and Flamm, K. 1996. "Technical progress and co-invention in computing and in the uses of computers," *Brookings Papers on Economic Activity. Microeconomics*), pp 1-83.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. 2002. "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *The Quarterly Journal of Economics* (117:1) Mar 01, pp 339-376.

Brown, C. L., and Krishna, A. 2004. "The Skeptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice," *Journal of Consumer Research* (31:3) Dec, pp 529-539.

Brown, L. D., and Pinello, A. S. 2007. "To what extent does the financial reporting process curb earnings surprise games?," *Journal of Accounting Research* (45:5), pp 947-981.

Bukata, R. 2013. "Unintentional Fraud: The Slippery Slope of EMR Up-Coding," in *epmonthly.com*.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., and Blumenthal, D. 2011. "The Benefits Of Health Information Technology: A Review Of The Recent Literature Shows Predominantly Positive Results," *Health Affairs* (30:3), pp 464-471.

CBO 2008. "Evidence on the Costs and Benefits of Health Information Technology," *Congressional Budget Office*) Jun.

CDC 2016. "Meaningful Use ".

Centers for Medicare & Medicaid Services 2010. "National Health Expenditure Projections 2010-2020."

Centers for Medicare & Medicaid Services 2015a. "CMS Roadmaps for the Traditional Fee-for-Service (FFS) Program: Overview ".

Centers for Medicare & Medicaid Services 2015b. "Statement of Work for the Recovery Audit Program," in *cms.gov*.

Centers for Medicare and Medicaid Services 2013. "Recovery auditing in the Medicare and Medicaid programs for fiscal year 2013."

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., Morton, S. C., and Shekelle, P. G. 2006. "Systematic review: impact of health information technology on quality, efficiency, and costs of medical care," *Annals of Internal Medicine* (144:10), pp 742-752.

Chertow, G. M., Lee, J., Kuperman, G. J., Burdick, E., Horsky, J., Seger, D. L., Lee, R., Mekala, A., Song, J., and Komaroff, A. L. 2001. "Guided medication dosing for inpatients with renal insufficiency," *Jama* (286:22), pp 2839-2844.

Clegg, C., Axtell, C., Damodaran, L., Farbey, B., Hull, R., Lloyd-Jones, R., Nicholls, J., Sell, R., and Tomlinson, C. 1997. "Information technology: a study of performance and the role of human and organizational factors," *Ergonomics* (40:9), pp 851-871.

Connolly, C. 2005. "Cedars-Sinai Doctors Cling to Pen and Paper."

Cornia, P. B., Amory, J. K., Fraser, S., Saint, S., and Lipsky, B. A. 2003. "Computer-based order entry decreases duration of indwelling urinary catheterization in hospitalized patients," *The American Journal of Medicine* (114:5), pp 404-407.

Danziger, S., Levav, J., and Avnaim-Pesso, L. 2011. "Extraneous factors in judicial decisions," *Proceedings of the National Academy of Sciences* (108:17), pp 6889-6892.

Dechow, P. M., Sloan, R. G., and Sweeney, A. P. 1996. "Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC," *Contemporary Accounting Research* (13:1), pp 1-36.

Devaraj, S., and Kohli, R. 2000. "Information technology payoff in the health-care industry: a longitudinal study," *Journal of Management Information Systems* (16:4), pp 41-67.

Dewar, R. D., and Dutton, J. E. 1986. "The adoption of radical and incremental innovations: an empirical analysis," *Management Science* (32:11), pp 1422-1433.

Dexter, P. R., Perkins, S. M., Maharry, K. S., Jones, K., and McDonald, C. J. 2004. "Inpatient computer-based standing orders vs physician reminders to increase influenza and pneumococcal vaccination rates: a randomized trial," *JAMA* (292:19), pp 2366-2371.

Dickhaut, J. W., McCabe, K. A., and Mukherji, A. 1995. "An experimental study of strategic information transmission," *Economic Theory* (6:3), pp 389-403.

Dranove, D., Forman, C., Goldfarb, A., and Greenstein, S. 2012. "The Trillion Dollar Conundrum: Complementarities and Health Information Technology.," *American Economic Journal: Economic Policy* (6:4), pp 239-270.

Duggan, M. 2002. "Hospital market structure and the behavior of not-for-profit hospitals," *RAND Journal of Economics* (33:3), pp 433-446.

Ebbes, P., Wedel, M., Böckenholt, U., and Steerneman, T. 2005. "Solving and testing for regressor-error (in) dependence when no instrumental variables are available: With new evidence for the effect of education on income," *Quantitative Marketing and Economics* (3:4), pp 365-392.

Ein-Dor, P., and Segev, E. 1978. "Organizational Context and the Success of Management Information Systems," *Management Science* (24:10) Jul 01, pp 1064-1077.

Ein-Dor, P., and Segev, E. 1982. "Organizational Context and MIS Structure: Some Empirical Evidence," *MIS quarterly* (6:3).

Ewusi-Mensah, K., and Przasnyski, Z. H. 1991. "On Information Systems Project Abandonment: An Exploratory Study of Organizational Practices," *MIS Quarterly* (15:1) Apr, p 67.

Fisher, E. S., Bynum, J. P., and Skinner, J. S. 2009. "Slowing the growth of health care costs—lessons from regional variation," *New England Journal of Medicine* (360:9), pp 849-852.

Fisher, E. S., Staiger, D. O., Bynum, J. P., and Gottlieb, D. J. 2007. "Creating accountable care organizations: the extended hospital medical staff," *Health Affairs* (26:1), pp w44-w57.

Garg, A. X., Adhikari, N. K. J., McDonald, H., Rosas-Arellano, M. P., Devereaux, P. J., Beyene, J., Sam, J., and Haynes, R. B. 2005. "Effects of Computerized Clinical Decision Support Systems on Practitioner Performance and Patient Outcomes: A Systematic Review," *Jama* (293:10) Apr 09, pp 1223-1238.

Gigerenzer, G. 2008. "Why heuristics work," *Perspectives on psychological science* (3:1), pp 20-29.

Gottlieb, M., Eichenwald, K., and Barbanel, J. 1997. "Health care’s giant: powerhouse under scrutiny—a special report.," 28 March.

Government Accountability Office 2011. "Effective Implementation of Recent Laws and Agency Actions Could Help Reduce Improper Payments ".

Greenwood, B. N., and Agarwal, R. 2015. "A Double Digital Divide? Two-Sided Markets and HIV Incidence among the Digitally Disadvantaged," *Management science* (Forthcoming).

Greenwood, B. N., Agarwal, R., Agarwal, R., and Gopal, A. 2016. "The When and Why of Abandonment: The Role of Organizational Differences in Medical Technology Lifecycles," *Available at SSRN*).

Harris, J. E. 1977. "The internal organization of hospitals: some economic implications," *The Bell Journal of Economics* (8:2), pp 467-482.

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., and Taylor, R. 2005. "Can electronic medical record systems transform health care? Potential health benefits, savings, and costs," *Health Affairs* (24:5), pp 1103-1117.

HIMSS 2011. "U.S. EMR Adoption Model,") Aug 11, pp 1-1.

HIMSS 2014. "HIMSS Analytics Definitions."

Hochstrasser, B., and Griffiths, C. 1991. *Controlling IT investment: strategy and management*, (

Huang, S. S., Avery, T. R., Song, Y., Elkins, K. R., Nguyen, C. C., Nutter, S. K., Nafday, A. S., Condon, C. J., Chang, M. T., and Chrest, D. 2010. "Quantifying interhospital patient sharing as a mechanism for infectious disease spread," *Infection Control and Hospital Epidemiology* (31:11), pp 1160-1169.

Huh, Y. E., Vosgerau, J., and Morewedge, C. K. 2014. "Social Defaults: Observed Choices Become Choice Defaults," *Journal of Consumer Research* (41:3), pp 746-760.

Hunton, J. E., Libby, R., and Mazza, C. L. 2006. "Financial reporting transparency and earnings management," *The Accounting Review* (81:1), pp 135-157.

Johnson, E. J., Bellman, S., and Lohse, G. L. 2002. "Defaults, Framing and Privacy: Why Opting In-Opting Out," *Marketing Letters* (13:1) Mar 01, pp 5-15.

Johnson, E. J., and Goldstein, D. 2003. "Do defaults save lives?," *Science* (302:5649) Nov 21, pp 1338-1339.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. 1991. "The endowment effect, loss aversion, and status quo bias," *Journal of Economic Perspectives* (5:1), pp 193-206.

Kahneman, D., and Tversky, A. 1982. "The psychology of preferences," *Scientific American* (246:1), pp 160-173.

Katz, M. L., and Shapiro, C. 1985. "Network Externalities, Competition, and Compatibility," *The American Economic Review* (75:3) Feb 01, pp 424-440.

Kearney, A. 1990. "Barriers to the successful application of information technology," *Department of Trade and Industry, London*).

Kim, Y., Lee, Z., and Gosain, S. 2005. "Impediments to successful ERP implementation process," *Business Process Management Journal* (11:2), pp 158-170.

Lammers, E. J., Adler-Milstein, J., and Kocher, K. E. 2014. "Does Health Information Exchange Reduce Redundant Imaging? Evidence From Emergency Departments," *Medical Care* (52:3), pp 227-234.

Lee, B. Y., McGlone, S. M., Song, Y., Avery, T. R., Eubank, S., Chang, C.-C., Bailey, R. R., Wagener, D. K., Burke, D. S., and Platt, R. 2011. "Social network analysis of patient sharing among hospitals in Orange County, California," *American Journal of Public Health* (101:4), pp 707-713.

Lee, J., McCullough, J. S., and Town, R. J. 2013. "The impact of health information technology on hospital productivity," *The RAND Journal of Economics* (44:3), pp 545-568.

Lehman, M. M. 1978. *Programs, cities, students—limits to growth?*, (Springer.

Lehman, M. M., and Belady, L. A. 1985. *Program evolution: processes of software change*, (Academic Press Professional, Inc.

Levav, J., Heitmann, M., Herrmann, A., and Iyengar, S. S. 2010. "Order in product customization decisions: Evidence from field experiments," *Journal of Political Economy* (118:2), pp 274-299.

Leviss, J., Gugerty, B., Association, A. H. I. M., and Association, A. M. I. 2010. *HIT Or Miss: Lessons Learned from Health Information Technology Implementation*, (AHIMA Press.

Lewis, C. E. 1969. "Variations in the incidence of surgery," *The New England journal of medicine* (281:16), pp 880-884.

Li, B. 2014. "Cracking the codes: do electronic medical records facilitate hospital revenue enhancement."

Lyytinen, K., and Hirschheim, R. 1987. "Information Systems Failures-A Survey And Classification of the Empirical Literature," in *Oxford Surverys in Information Technology*, pp. 257-309.

Markus, M. L., Steinfield, C. W., and Wigand, R. T. 2006. "Industry-wide information systems standardization as collective action: the case of the US residential mortgage industry," *MIS Quarterly* (30:Special Issue), pp 439-465.

McCullough, J. S., Casey, M., Moscovice, I., and Prasad, S. 2010. "The Effect Of Health Information Technology On Quality In U.S. Hospitals," *Health Affairs* (29:4) May 05, pp 647-654.

McCullough, J. S., Parente, S., and Town, R. 2013. "Health Information Technology and Patient Outcomes: The Role of Organizational and Information Complementarities," *NBER Working Paper Series*) Feb 21, pp 1-47.

McCullough, J. S., Parente, S., and Town, R. 2016. "Health Information Technology and Patient Outcomes: The Role of Organizational and Information Complementarities," *The RAND Journal of Economics* (47:1) Feb 21, pp 207-236.

McDaniel, L., Martin, R. D., and Maines, L. A. 2002. "Evaluating financial reporting quality: The effects of financial expertise vs. financial literacy," *The Accounting Review* (77:s-1), pp 139-167.

McPherson, K., Strong, P., Epstein, A., and Jones, L. 1981. "Regional variations in the use of common surgical procedures: within and between England and Wales, Canada and the United States of America," *Social Science & Medicine. Part A: Medical Psychology & Medical Sociology* (15:3), pp 273-288.

Merton, R. K. 1936. "The Unanticipated Consequences of Purposive Social Action," *American sociological review* (1:6) Dec 01, pp 894-904.

Miller, A. R., and Tucker, C. E. 2011. "Can Health Care Information Technology Save Babies?," *The Journal of Political Economy* (119:2) May, pp 289-324.

Moch, M. K., and Morse, E. V. 1977. "Size, Centralization and Organizational Adoption of Innovations," *American sociological review* (42:5) Oct 01, pp 716-725.

Nah, F. F.-H., Lau, J. L.-S., and Kuang, J. 2001. "Critical factors for successful implementation of enterprise systems," *Business Process Management Journal* (7:3), pp 285-296.

Nuance 2015. "Computer Assisted Physician Documentation."

Obama, B. 2009. "Inaugural Address," USA.

Overhage, J. M., Tierney, W. M., Zhou, X.-H. A., and McDonald, C. J. 1997. "A randomized trial of “corollary orders” to prevent errors of omission," *Journal of the American Medical Informatics Association* (4:5), pp 364-375.

Park, C. W., Jun, S. Y., and MacInnis, D. J. 2000. "Choosing what I want versus rejecting what I do not want: An application of decision framing to product option choice decisions," *Journal of Marketing Research* (37:2), pp 187-202.

Petrucci, K., Petrucci, P., Canfield, K., McCormick, K., Kjerulff, K., and Parks, P. Year. "Evaluation of UNIS: urological nursing information systems," Proceedings of the Annual Symposium on Computer Application in Medical Care, American Medical Informatics Association1991, p. 43.

Poissant, L., Pereira, J., Tamblyn, R., and Kawasumi, Y. 2005. "The impact of electronic health records on time efficiency of physicians and nurses: a systematic review," *Journal of the American Medical Informatics Association* (12:5), pp 505-516.

Ransbotham, S., Overby, E., and Jernigan, M. 2013. "Do Electronic Medical Records Reduce Medical Malpractice Claim Resolution Time?," in *Workshop on Health IT and Economics*: College Park, MD.

Reed, A., and Creswell, J. 2012. "U.S. Warning to Hospitals on Medicare Bill Abuses," September 25, 2012 (available at http://www.nytimes.com/2012/09/25/business/us-warns-hospitals-on-medicare-billing.html).

Rhyne, L. C. 1985. "The relationship of information usage characteristics to planning system sophistication: an empirical examination," *Strategic Management Journal* (6:4), pp 319-337.

Samore, M., Lichtenberg, D., Saubermann, L., Kawachi, C., and Carmeli, Y. 1997. "A clinical data repository enhances hospital infection control.,"), p 56.

Scott, J. T., Rundall, T. G., Vogt, T. M., and Hsu, J. 2005. "Kaiser Permanente’s experience of implementing an electronic medical record: a qualitative study," in *BMJ: British Medical Journal*, pp. 1313-1316.

Sidorov, J. 2006. "It ain’t necessarily so: the electronic health record and the unlikely prospect of reducing health care costs," *Health Affairs* (25:4), pp 1079-1085.

Silverman, E., and Skinner, J. 2004. "Medicare upcoding and hospital ownership," *Journal of Health Economics* (23:2), pp 369-389.

Soh, C., and Sia, S. K. 2004. "An institutional perspective on sources of ERP package–organisation misalignments," *The Journal of Strategic Information Systems* (13:4), pp 375-397.

Thong, J. Y. 1999. "An integrated model of information systems adoption in small businesses," *Journal of Management Information Systems* (15:4), pp 187-214.

Tierney, W. M., Miller, M. E., and McDonald, C. J. 1990. "The effect on test ordering of informing physicians of the charges for outpatient diagnostic tests," *New England Journal of Medicine* (322:21), pp 1499-1504.

Torio, C. M., and Andrews, R. M. 2013. "National inpatient hospital costs: the most expensive conditions by payer, 2011,").

United States Senate Committee on Finance 2015. "Hatch Statement at Finance Hearing on Medicare Audit and Appeals."

US Congress 2009. "Health Information Technology for Economic and Clinical Health (HITECH) Act."

Utterback, J. M. 1974. "Innovation in industry and the diffusion of technology," *Science* (183:4125), pp 620-626.

Venkataraman, R., Weber, J. P., and Willenborg, M. 2008. "Litigation risk, audit quality, and audit fees: Evidence from initial public offerings," *The Accounting Review* (83:5), pp 1315-1345.

Welch, W. P., Miller, M. E., Welch, H. G., Fisher, E. S., and Wennberg, J. E. 1993. "Geographic variation in expenditures for physicians' services in the United States," *New England journal of medicine* (328:9), pp 621-627.

Wennberg, J. E., Cooper, M. M., and Birkmeyer, J. 1999. "The quality of medical care in the United States: a report on the Medicare program," p. 6.

Wennberg, J. E., Fisher, E. S., Stukel, T. A., Skinner, J. S., Sharp, S. M., and Bronner, K. K. 2004. "Use of hospitals, physician visits, and hospice care during last six months of life among cohorts loyal to highly respected hospitals in the United States," *Bmj* (328:7440), p 607.

White, R. H., Hong, R., Venook, A. P., Daschbach, M. M., Murray, W., Mungall, D. R., and Coleman, M. R. W. 1987. "Initiation of warfarin therapy," *Journal of General Internal Medicine* (2:3), pp 141-148.

Yale Medical Group 2012. "Teaching Physician Compliance," in *Yale Medical Group*.

Zhang, J., Wedel, M., and Pieters, R. 2009. "Sales effects of attention to feature advertisements: a Bayesian mediation analysis," *Journal of Marketing Research* (46:5), pp 669-681.

Zhu, K., Kraemer, K. L., Gurbaxani, V., and Xu, S. X. 2006. "Migration to open-standard interorganizational systems: network effects, switching costs, and path dependency," *MIS Quarterly* (30), pp 515-539.