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Essays on the Impacts of Health Information Technology

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M.S. in Consumer Behavior, Purdue University

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An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
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Abstract

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The purpose of this dissertation is to investigate the emerging role of health information technology in influencing various measures of hospital performance from a multilevel perspective. While there are extensive studies on this matter, it is quite inconclusive as to why implementation of EHR is not automatically linked to enhanced performance. In continuing discussion on the impacts of Electronic Health Records as a special type of HIT, this dissertation calls for more attention on largely overlooked aspect of HIT implementation - "the context." Three essays in this dissertation explore how the existing contextual factors can modify the expected benefits of EHR using various econometrics techniques.

The first essay of my dissertation investigates whether US hospitals are ready for new EHR implementation. As a first step toward governmental EHR incentive program (HITECH Act), I viewed the existing HIT infrastructures in administrative and clinical units can be meaningful indicators for their technical readiness toward EHR implementation. Results indicate that the current HIT infrastructure among US hospitals only supports for much basic functionalities of EHR and as EHR becomes more complicated, US hospitals seem to employ intangible non-HIT resources to cope with EHR-induced challenges.

The second essay of my dissertation examines how the value of EHR is translated into individual patients' length of stay within a hospital. By considering "a care service triad" in which a care provider, a patient, and EHR features are encountered, I investigate the impacts of interactions of such entities on a patient's length of stay. Results suggest that as hospitals selectively adopted EHR features, the benefits of each feature of EHR are differentially moderated by the focal hospital's existing care conditions– hospital care focus, physician workload, care complexity and patient severity. Such results also largely vary with patient heterogeneity with short-medium-long length of stay.

The third essay of my dissertation explores how department level EHR implementation can enhance emergency department (ED) performance. I particularly look at the existing ED information capability as a key mediation mechanism in the link between EHR and ED performance. Results show that in the first round of wait time upon arrival, HIE-mediated EHR is shown to reduce some measures of wait time. In another round of wait time for final disposition, clinical process integration-mediated EHR is likely to reduce wait time for hospital admission. However, such performance effects selectively arise under certain mediation mechanisms.

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May God bless you all.

"Your beginnings will seem humble, so prosperous will your future be (Job 8:7)."

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Chapter 1

Overview

1.1. Introduction

In recent years, there have been growing expectations on emerging roles of information technology (IT) in the US healthcare. Under the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 initiatives, eligible US healthcare organizations have increasingly involved in selection, implementation and use of HIT to meet the staged HIT use initiatives, hoping for better quality of care, patient safety, and better organizational performance. Against this backdrop, the initial attestation results from the aforementioned incentive programs have largely disappointed healthcare policy makers and practitioners. Dubbed as anew "HIT productivity paradox," healthcare stakeholders began to doubt that a considerable HIT implementation does not lead to better care outcomes and organization performance (Lapointe et al. 2010).

However, HIT implementation is characterized by its surrounding contexts and without careful considerations on this, measuring HIT impacts might be misleading. In fact, healthcare consists of multi-stakeholders from patients, care team, organizations and its surrounding environment (National Research Council 2005). As a main source of health information comes from heterogeneous patients and the outcome is a person's life or death, information management and information exchange among multi-stakeholders are very crucial to the delivery of care and therefore, HIT is expected to transform the way information is created and shared within and between healthcare organizations. Therefore, the value of HIT is greatly influenced by the characteristics of the multi-stakeholders and various care contexts. Furthermore, definition of HIT varies between and within healthcare organizations. Between the organizations, definition of HIT may vary along with off-the-shelf vs. in-house HIT products and the features provided by various vendors. Within the organizations, such definition of what comprises HIT can also differ. At hospital level, healthcare administrators may consider HIT as a big piece of technology such that they may care whether they have "it" or not. At group level, selective care givers use some subset of HIT and they expect their performance enhancement. At individual level, each individual uses subsets of HIT features, expecting better individual performance.

Under this context, without clear consensus on the context in which the focal HIT is employed and defined, it might be too early to conclude the performance benefits of HIT. In this three-essay dissertation, I showcase the impact of the same HIT at multiple levels of a healthcare organization, especially in a hospital context. With varying definitions of HIT and mechanisms that work in that specific context at each level, these essays complement one another to answer the overarching research question –Does HIT enhance hospital performance?

1.2. Overview on Health Information Technology

In order to better understand HIT, one needs to understand what IT is and how it creates value in other contexts. Information Technology (IT) is a critical resource in facilitating organizational performance. In general, IT is known to create value with various complementary resources whose value is manifested in various performance metrics (Roberts and Grover 2012). For example, IT investment can allow firms to achieve productivity as well as profitability such as revenue growth and cost savings *at firm level* (e.g. Kauffman and Walden 2001; Mithas et al. 2011), streamlined group decision making *at group level* (e.g. Davenport and Short 1990), enhanced task performance *at individual level* (e.g. Goodhue and Thompson 1995). However, such IT impacts are also realized under certain condition - an idiosyncratic context in which the organizations continuously do their business, groups interact and communicate, and each individual performs her various tasks.

Healthcare context epitomizes the importance of the aforementioned conditions which is imperative to understand the value of IT. IT in this sector, or health IT (HIT) is the domain specific IT and the term HIT has been interchangeably used as referring to electronic health records (EHR) as well as health information exchange (HIE). Here, EHR is defined as a set of technologies that involve the exchange of health information in an electronic environment whereas HIE allows various health care providers and patients to appropriately access and securely share a patient's vital medical information electronically (Department of Human and Health Services). In a healthcare context, information management and information exchange are crucial to all levels of the healthcare organizations (National Research Council 2005) and implementation of one HIT system can have differential implications on patients, care teams, healthcare organizations (e.g. hospitals and office-based physicians) and the environment. Therefore, it is fair to say that the value of EHR and HIE may not be realized collectively within the focal organization but selectively and differentially across different levels of the organization.

Although interdisciplinary researchers and healthcare practitioner have paid extensive attention on investigating the adoption and impacts of HIT including EHR and

HIE, the results on whether and how HIT improves performance have been largely inconclusive (Agarwal et al. 2010). The growing consensus is that contextual difference might be a major reason for such equivocal results (Fichman et al. 2012). Throughout this dissertation, therefore, I focus on three major contextual differences to investigate the impacts of EHR and HIE on hospital performance. First, healthcare is influenced by rules and regulations in a location. Second, interdependence among HIT components and heterogeneity in healthcare organizations need to be carefully considered (Agarwal et al. 2010). Third, patient-oriented hospital service require information quality and its local IT capability to improve patient care.

1.3. Agenda of the Dissertation

Taken together, I examine the impacts of EHR and HIE at multiple levels of a hospital with full consideration of the aforementioned contextual differences. Consistent with HIT impact research, the overarching research question of this dissertation is "Do EHR and HIE improve patient care outcome and enhance hospital performance?" More specifically, the first essay considers the value creation of EHR in concert with the ex ante HIT infrastructure *at firm level*. As a hospital has idiosyncratic care plans and patient population, the adoption and implementation of various *ex ante* HIT systems have shaped the overall HIT capability of the hospital. The first essay asks a question "Why does the value of EHR differ across hospitals?" To answer this question, this study identifies the complementary relationships between EHR and the existing HIT infrastructure capability and empirically examines its downstream effect on hospital productivity and profitability. Next, the second essay focuses on the differential impacts of EHR feature use *at patient level*. In a hospital, there are myriad care service dyads between care providers and a patient where there exists a tension on how idiosyncratic patient information can be utilized and result in better care outcomes. In the process of care provision, the use of specific EHR features can help care providers to cope with various care tasks and improve patient care outcome. The second essay thus asks "Why does the value of EHR differ across patients in a hospital?" Particularly, this study explicitly tests the fit between care tasks and EHR feature use in explaining variations in clinical outcome at patient level. Lastly, the third essay delineates the mediated impacts of EHR on group-level performance, especially in a hospital-based emergency department. As each hospital-based emergency department (ED) has uniquely maintained existing information capability of ED process, in this case, EHR may not directly influence ED performance but indirectly through selectively aligning with the existing ED information processing capability. Therefore, the third essay investigates the mediated impacts of EHR implementation on various measures of ED wait time *at group level*.

Chapter 2

Measuring the Impacts of HIT on Hospital Productivity and Profitability

2.1. Introduction

The potential for electronic health records (EHR) to improve health care delivery as well as hospital operating performance has been widely recognized (Chaudry et al. 2006, Blumenthal et al. 2007, DesRoches et al. 2008). Electronic health records are digital versions of health charts that contains all of a patient's medical history along with some information processing and knowledge support applications such as clinical data repository (CDR), computerized practitioner order entry (CPOE), and clinical decision support systems (CDSS) (Hannan 1999, HealthIT.gov). With the passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, hospitals in the United States have continued to invest in EHR to create an electronic data repository as well as to automate and streamline patient workflows.

Despite the sizeable investments in EHR, there is continuing debate and skepticism about the value of these investments and whether they can truly improve hospital performance. The sentiment amongst researchers and healthcare administrators is that the industry-wide transformational effects of EHR have not progressed at the expected pace and that the benefits of EHR are yet to be fully realized (Agarwal et al. 2010, Jha 2011, Fichman et al. 2011, Lucas et al. 2013). In addressing this concern, there has been a spate of recent research on the effects of EHR in improving varied performance metrics including care quality, utilization of care, revenue enhancement and cost reduction within hospitals (see Chaudry et al. 2006, Agarwal et al. 2010 for contemporary reviews). However, these studies have focused largely on the main effects of EHR and barring some notable exceptions (e.g. Dranove et al. 2012, McCullough et al. 2013), the underlying mechanisms through which EHR enhances hospital performance remain underexplored.

At the intersection of the business value of IT and healthcare literature, this paper develops a model to link EHR and hospital performance and makes two important contributions. First, we posit that the value of EHR is realized through complementarities with the existing HIT infrastructure that serves as a foundation of shared technical components and IT services for building a hospital's administrative and clinical applications (Weil et al. 2002). Although prior IS literature has extensively emphasized the importance of the quality and flexibility of IT infrastructure for timely response to business needs and directions (Duncan 1995, Broadbent et al. 1999), relatively little empirical attention has been paid to the direct as well as indirect performance effects of IT infrastructure (e.g. Mithas et al. 2011). More specifically, in a hospital context, the indirect roles of IT infrastructure (hereafter, HIT infrastructure) becomes even more salient. Since EHR "involves the exchange of health information in an electronic environment" (Department of Human and Health Services) by linking the idiosyncratic administrative and clinical functions of a hospital (Goldschmidt 2005, Menachemi and Brooks 2006, HIMSS 2009), the *ex ante* HIT infrastructure in the two units (see Figure 1) determines not only the timely implementation but also the utilization of the full functionalities of EHR. Therefore, we focus on the two decomposable HIT infrastructures in the administrative and clinical units of a hospital and empirically test their downstream effects on hospital performance. Specifically, we examine both two-way and three-way complementarities of EHR with the administrative and clinical HIT infrastructures respectively.

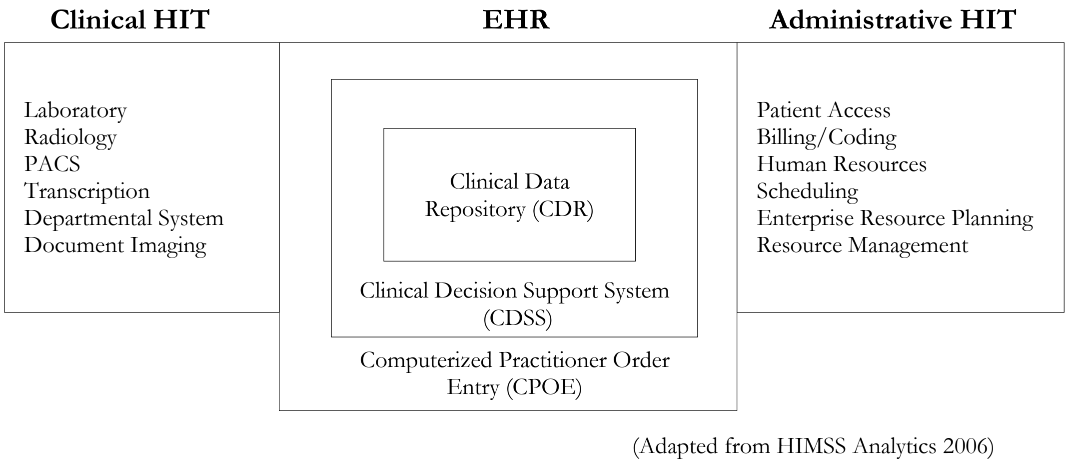

Figure 1. The Relational View of EHR and HIT Infrastructures

Second, we provide one of the first formal expositions of spatial statistics in IS research, a technique that is well established and often used in Marketing and geographic information systems (GIS) area but not typically utilized in the IS research domain. Hospitals generally provide care services to patients in the local population such that the flow of regional patient population leads to competitions with other healthcare providers in close proximity (Santarre and Neun 2006). Since a hospital location is quasi-fixed over time, competition and interactions among healthcare providers within the region are common but largely unobserved. Moreover, this regional confounding factor is shown to simultaneously affect a hospital's adoption of EHR (Angst et al. 2010) as well as overall performance in the geographic location (Santarre and Neun 2006). To rule out these biases, we introduce a spatial error model (SEM) which is more efficient in explaining spatial bias when compared with traditional OLS regression techniques. We test the proposed complementarity relationships between EHR and the HIT infrastructure by triangulating data from the Office of Statewide Health Planning and Development (OSHPD) with Healthcare Information and Management Systems Society (HIMSS) Analytics during 2002-2010.

Results from our study show that the two-way complementarities of basic EHR with administrative HIT as well with clinical HIT infrastructures differentially enhance hospital performance. While the three-way complementarities positively influence patient volume of a hospital in the locale, our results indicate that only the HIT intensive hospitals are able to translate the increased patient volume into net patient revenue. The results are also examined and verified by propensity score matched samples to control for potential selection bias in the data.

The remainder of this paper is organized as follows. In the next section, we develop the research model and key hypotheses. Next, we describe our data and research variables followed by empirical analysis and results. Finally, we conclude the paper with a discussion of implications for research and practice, as well as directions for future work.

2.2. Theoretical Background

2.2.1. Review of the Literature on HIT Infrastructure

The academic literature on the business value of IT has posited that an organization's IT infrastructure enables the development and rapid deployment of new applications, allowing it to respond to emerging opportunities or to neutralize competitive threats (Duncan 1995, Broadbent and Weil 1997, Ray et al. 2005). A firm's IT infrastructure equips it with the 'platform readiness' capability to launch new business applications, provides ready access to the relevant data, and effectively networks with other systems to reduce cost for current and future innovation (Duncan 1995). For this reason, a firm's IT infrastructure is regarded as a fundamental complementary resource for facilitating future business initiatives (e.g. Armstrong and Sambamurthy 1999, Broadbent et al. 1999, Sambamurthy et al 2003) and effective integration between IT infrastructure and new business initiatives positively influences firm performance (e.g. Chatterjee et al. 2002, Zhu and Kraemer 2002, Zhu 2004, Rai et al. 2006, Aral and Weil 2007).

A review of the extensive literature on IT infrastructure reveals a number of important ideas that have emerged from prior studies (see Table 1 for the dimensions and performance impacts of IT infrastructure). First, the term IT infrastructure has been used to broadly describe a *collective* arrangement of shared technical components and IT services including platforms, networks, telecommunications, data and software applications (Duncan 1995), as well as a *selective* set of shared tools that support specific functionality of the organization (Roberts and Grover 2012). Second, IT infrastructure is often viewed as being monolithic in an organization and characteristics of the quality of the infrastructure, measured in terms of its *flexibility* (e.g. Duncan 1995, Ray et al. 2005), *sophistication* (e.g. Armstrong and Sambamurthy 1999), the *level of integration* (e.g. Bharadwaj 2000) and *intra-/inter-connectivity* (e.g. Zhu and Kraemer 2002, Zhu 2004, Rai et al. 2006, Tanriverdi 2006) have been examined in a wide array of industry sectors such as manufacturing, retail, bank, and petroleum (cf. Broadbent et al. 1999). Lastly, the quality of the IT infrastructure has been viewed as an important precursor to a firm's overall IT capability (Bharadwaj 2000, Aral and Weil 2007) and also as an antecedent construct to other organizational capabilities such as customer management and process management capabilities (Mithas et al. 2011) and customer agility in hypercompetitive environment (Roberts and Grover 2012). In summary, IT infrastructure has been generally regarded as a monolithic construct in IS literature and several studies have examined both the direct impact of IT infrastructure (e.g. Ray et al. 2005) as well as its indirect impacts on organization performance (e.g. Zhu and Kraemer 2002, Zhu 2004).

Table 1. The Dimensionality and Performance Impacts of IT Infrastructure

		Dimensionality	
		Monolithic	Non-Monolithic
Performance Impacts	Direct	Armstrong and Sambamurthy (1999), Chatterjee et al. (2002), Ganesh et al. (2005), Ray et al. (2005)	Menon et al. (2009)*
	Indirect	Zhu and Kraemer (2002), Zhu (2004), Rai et al. (2006), Tanriverdi (2006), Aral and Weil (2007), Mithas et al. (2011)	Roberts and Grover (2012) Angst et al. (2013)* Dranove et al. (2012)*

* Studies in healthcare sector

Findings from this literature, however, only partially apply in the context of a hospital in which the IT infrastructure can no longer be viewed as a monolithic entity. Prior HIT research has described the HIT infrastructure in hospitals as having two distinct components as selective subsets of a broader technology platform, namely, an administrative health IT infrastructure (AHIT) and a clinical health IT infrastructure (CHIT), each supporting the two distinct sides of a hospital's overall operations (Menon et al. 2009, Angst et al. 2012). Hospitals have long been recognized as "two firms in one" (Harris 1977), meaning that a hospital's administrative and clinical units remain disjoint, with the former run by hospital administrators and the latter run by doctors. Described as a loosely-coupled organization (Weick 1976), the administrative and clinical units of a hospital maintain their distinct identities while overall interdependency is preserved for tightly-knit patient care. The split in authority across the two sides of a hospital has also been emphasized in the organizational literature (see for example

Orton and Weick 1990, Tucker et al. 2007) with the net result that the two sides have their own distinct objectives, pricing strategies, and constraints (Harris 1977). Not surprisingly, the disjointed organizational structure is also reflected in a hospital's underlying IT infrastructure such that the administrative and clinical IT infrastructures have typically evolved independently and seldom provide a shared and seamless platform of interconnectivity across the entire hospital operations (National Research Council 2005). It is in this context that the implementation of an EHR system has to be considered.

The AHIT infrastructure in hospitals is designed to support the administrative functions and related data access, such as, documenting patient information, processing billing and claims, communicating with other departments and managing organizational resources. The CHIT infrastructure, on the other hand, is designed to support the diagnostic, prognostic, and follow-up care services i.e. developing treatment plans, prescribing medication, ordering clinical procedures, and pre-/post care activities (e.g. scheduling hospital visits, recording patients' medical history, educating patients) (Bowen et al. 2010). In addition to their differential functions, these two infrastructures have also exhibited differential adoption and implementation patterns. Although software and hardware markets for HIT are considered to be less mature (National Research Council. 2005), many hospitals have generally tended to adopt the AHIT infrastructure components at a much faster pace when compared to the CHIT infrastructure components (RAND 2005, HIMSS 2011). Together with these disparate innovation patterns, the AHIT and CHIT infrastructure have directly or indirectly led to differential performance gains (Borzekowski 2009, Angst et al. 2012, Bardhan and Thouin 2013). For example, Menon et al. (2009) found that investments in CHIT directly led to more immediate productivity improvement, whereas AHIT investments took a much longer time to accrue such gains. Therefore, we posit that these two infrastructures disproportionately complement the effects of EHR such that the impacts of integration of EHR with AHIT infrastructure may differ from those with CHIT infrastructure as well as from the joint (three-way) integration of the two HIT infrastructures and EHR under this structure.

2.2.2. Review of the Literature on Electronic Health Records (EHR)

Electronic health records are characterized by three main properties- electronic connectivity, interdependence with other HIT systems, and location dependency (see Agarwal et al. 2010 for review of the literature). First, EHR has the potential to enable electronic communication and connectivity within hospital units and between other healthcare organizations (Blumenthal 2007). The interconnected health data, enabled by EHR implementation, is expected to not only enable the hospital's administrative and clinical units to coordinate and better manage patient care services but also to better communicate with other care providers in the location and further participate in national-level health information exchange (HIE) (Center for Medicare and Medicaid Services). Thus, a hospital's internal electronic connectivity can be an important precursor to external electronic connectivity among various healthcare providers. Second, EHR is systemically interdependent which requires seamless integration with the existing HIT systems (Goldschmidt 2005, Menachemi and Brooks 2006, Agarwal et al. 2010, see Figure 1 for the interdependence of EHR). For example, when EHR is fully integrated with the radiology system, it can improve clinical process lead time, financial revenues and physician satisfaction (e.g. Ayal and Seidmann 2009). Thus, measuring the main effects of EHR may provide an incomplete picture of performance impacts from EHR implementation. Lastly, the adoption and implementation of EHR are influenced by various location-based conditions such as local healthcare law and regulation

(Miller and Tucker 2009), the regional level of IT intensity (Dranove et al. 2012) and the adoption of EHR by neighboring healthcare organizations in the location (RAND 2005, Angst et al. 2010, Lee et al. 2012, McCullough et al. 2013). These characteristics of EHR often work together such that while electronic connectivity is regarded as main mechanisms in enhancing various hospital performance, prior work has included other legacy HIT systems (e.g. Bardhan and Thouin 2013, Oh et al. 2012) or location dependency (e.g. Lee et al. 2012, Oh et al. 2012, Dranove et al. 2012, McCullough et al. 2013) as important covariates in explaining hospital performance variations of EHR.

While a growing body of literature has examined the sole impacts of EHR on differences in hospital performance (e.g. Borzekowski 2009, Furukawa et al. 2010, McCullough et al. 2010), the interdependent relationships between the two HIT infrastructures and EHR have been theoretically assumed and remain empirically under investigated. Some notable recent work has considered the complementary impacts of a hospital's *ex ante* HIT infrastructure measured by prior HIT investment (e.g. Dranove et al. 2012) or by the extant information management capability (McCullough et al. 2013) in enabling a hospital's EHR benefits. These studies implicitly assume EHRs to be an integral part of the clinical HIT infrastructure and therefore they mainly focus on the role of CHIT infrastructure on EHR effects. Although such a view has come to be accepted in prior HIT literature (e.g. National Research Council 2005, RAND 2005), we make the argument in this study, that over the course of patient care provisioning realizing the full potential of EHRs require its integration with both sides of a hospital , i.e., its AHIT and CHIT infrastructure. Yet, the performance impacts of EHR implementation in concert with the AHIT and CHIT infrastructures remains unexplored and therefore, is the specific focus of this paper, while simultaneously accounting for the *location dependency* of EHR.

Table 2. Literature Review on HIT and Hospital Performance

Author/Year	HIT Effects	HIT Variables	Covariates: Internal Factors	Covariates: Regional Factors	Hospital Performance	Findings
Devaraj & Kohli (2000)	Complementarities with other resources	IT investment (IT labor IT support, IT capital) Business process reengineering (BPR)	CMI Labor intensity (FTE) Medicare/Medicaid Outpatient mix Per-capital income	-	Profitability Net patient revenue per day Net patient revenue per admission Quality Mortality rate Customer satisfaction	Lags of IT investment, BPR, and complementarities affects hospital profitability and quality
Menon et al. (2000)	Main effect	IT labor/ non-IT labor IT capital Medical IT capital Medical capital	Ownership Teaching	-	Adjusted patient days Operating revenues	More inputs on IT capital and IT labor have positive effect on hospital productivity
Devaraj & Kohli (2003)	Main effect	Decision Support System (DSS) use	Medicare Medicaid CMI Patient income Employee FTE Hospital age Outpatients	-	Mortality Revenue per admission Revenue per day	The actual use (two month-lag) of DSS system leads to financial and quality performance of hospitals
Borzekowski (2009)	Main effect	Financial Administrative	Average hourly wage	-	Operating expenses	IT is associated with lower costs

		systems Clinical systems	Inpatient discharges Outpatient visits Fixed assets CMI			at the most automated hospitals The adoption of particular systems is associated with lower costs
Menon et al. (2009)	Main effect	Administrative IT Clinical IT	Medical capital Government status Profit status Teaching status Medicare status CMI	Urban status	Then number of patient days for employee Hospital charges per labor cost	Clinical HIT improve hospital output in the short run whereas administrative HIT takes longer to be effective on hospital productivity
Lee et al. (2012)	Main effect	Labor Capital IT labor IT capital	Ownership type	Neighbor's IT labor Neighbor's IT capital	Operating revenues (value-added)	Marginal effects of IT are high but the contribution to value-added is modest
Bardhan & Thouin (2013)	Main effect	Clinical systems Financial systems Scheduling systems Human resource systems	Bed size Hospital type Case mix index Teaching	Urban/rural	Process care quality Operating expenses	Clinical (+) Scheduling(+) HR (+) Financial (-)

Oh et al. (2012)	Main effect	Administrative IT Clinical IT Cardiology IT (among 18 systems)	<u>Patient level</u> # diagnoses # procedures Total charges Payer type Admission type Risk of mortality <u>Hospital level</u> Bed size Case mix index	Rural/urban Median income of patient Zip-code	Cardiac patients' readmission LOS	Administrative and cardiology applications are associated with a lower risk of 30-day readmissions only for above geometric mean patient group
Dranove et al. (2012)	Main & Complementarity effects	EHR Systems	Hospital characteristics	Local IT capability	Operating expenses per admission	EHR adoption is initially leads to increase in costs Urban hospitals have a decrease in costs after 3 years later
McCullough et al. (2013)	Complementarities with other resources	EHR CPOE eMAR PACS Utilization measures met for CPOE % pharmacy orders made electronically	Adjusted admissions, bed size, service scope, payer mix, multihospital system membership, ownership status <u>Patient level</u> Age gender, race, admission type	Neighboring hospitals' adoption of EMR and CPOE	60 day all-cause mortality Thirty-day readmission LOS	While no relationship between HIT and quality for average patient, IT improves outcomes for patients with complex, high-severity diagnoses

			Diagnostic measure Secondary diagnosis/primary diagnosis subcategories			
Devaraj et al. (2013)	Main effect	IT investment LOS Average LOS: swift flow StdDev LOS: even flow	Hospital size Utilization for profit status Hospital age Employee FTE	-	Patient revenue Mortality Complications	Swift and even patient flow positively influence hospital's net patient revenue, reduction in complications

2.2.3. Hospital Performance

Prior literature has examined the link between HIT and various measures of hospital performance (see Table 2 for a review of the literature on the link between HIT and hospital performance). The current research seeks to understand how the implementation of EHR in concert with the existing HIT infrastructures affects a hospital's productivity and financial performance. Given the complexity of hospital operations and the fact that selecting performance indicators in any one dimension provides an incomplete picture, scholars have emphasized the importance of measuring hospital performance along multiple dimensions (Devaraj and Kohli 2003). In keeping with this recommendation, we consider a hospital's performance along multiple measures of performance related to overall productivity and profitability.

Hospitals continue to adopt and implement HIT in order to enhance overall productivity and profitability subject to hospital-specific resource constraints. When an EHR is fully integrated with the two HIT infrastructures that complement the suggested functionalities of EHR, electronic communication and connectivity within and between clinical units can impact the service volume of a hospital. Reducing the coordination time (such as in pulling paper-based charts) and improving information sharing during hand-offs (such as transferring patients between units and dismissing patients at the end of care service) can improve efficiency and lead to productivity gains. Furthermore, the interconnectivity and flexibility of EHR can enable hospitals to automate repetitive tasks in administrative units and to identify and integrate disconnected area or processes in clinical units (Angst et al. 2012). Through such integration, hospitals become capable of monitoring performance metrics, improving clinical decision making, and producing more accurate billing and claims reports. Last but not least, reduction in medical errors and complications enabled by EHR can help hospitals decrease cost of care (Dranove et al. 2012). Therefore we expect that the EHR's electronic connectivity and data integration capability in conjunction with the analytical decision support capability will impact hospital's overall productivity as well as profitability.

2.2.4. The Complementary effects of EHR

Viewed from a complementarity perspective (Milgrom and Roberts 1995)[1], the primary claim of this paper is that any consideration of the potential impact of EHR systems would have to take into account a hospital's existing AHIT and CHIT infrastructure capabilities which could enable or inhibit the EHR's impact. In other words, EHR systems are more valuable to hospitals when they can be connected to other administrative and clinical support systems that are already in place, and conversely, hospitals lacking adequate technology infrastructures will be stymied in their efforts to derive the benefits of the new EHR investments.

2.2.4.1. Complementarities of EHR with AHIT Infrastructure

The main purpose of administrative HIT infrastructure is to equip hospital administrators with information management capabilities needed for hospital resource planning, hospital outcome monitoring and patient management. Prior work has documented that AHIT infrastructure enhances hospital performance (e.g. Setia et al. 2010, Bardhan and Thouin 2013) because administration's tasks for communicating, coordinating, controlling, and planning are automated through investment in AHIT infrastructure (Menon et al. 2009, Angst et al. 2012). When EHR is fully integrated with the AHIT infrastructure, such

[1] Complementarity theory posits that the value of an organizational resource increases when heterogeneous complementary resources coexist and/or are combined with the focal organizational resource (Milgrom and Roberts 1990, 1995). Complementary relationships in organizations have been extensively studied in various research disciplines (see Ennen and Ritcher 2010 for more details).

integration can produce more accurate record of diagnoses, lab tests, patient's lifestyle behaviors and habits (Optum Insight 2012) which in turn improve billing process by more accurate coding (Adler-Milstein et al. 2013). In other words, the tighter data sharing enables hospital administrative units to access real time clinical data, reduce the errors in billing and insurance claims, analyze organizational resource consumed per each care episode, and estimate future resource needs, which will positively influence hospital performance.

2.2.4.2. Complementarities of EHR with CHIT Infrastructure

The clinical HIT infrastructure is designed to provide clinical units with capabilities of care provision and coordination by creating and sharing clinical charts, tracking medication errors and nursing performance, capturing operating room data to improve processes, and sharing medical images and lab tests between care providers. Prior studies on the impacts of CHIT infrastructure on hospital performance have been equivocal, with some studies documenting a positive effect (e.g. Menachemi et al. 2006, Menon et al. 2009, Angst et al. 2012) and other studies finding a negative effect (e.g. Setia et al. 2010). Since CHIT infrastructure is widely known to be fragmented based on idiosyncratic functionalities across clinical departments (IOM 2001), healthcare practitioners have high expectations for the integration between EHR and CHIT infrastructure, which can connect isolated data across department and digitize various elements of patient care (Angst et al. 2012). More specifically, real time access to care history, test results and decision support systems enable care providers to develop effective and timely treatment plans. Moreover, as the patient information is accumulated and accessible over the course of each care episode, redundant and unnecessary communication can be reduced whereas the continuity of patient care via cross-departmental communication and diagnostic and prognostic efficiency can be enhanced. Therefore, integration of EHR with CHIT infrastructure can lead to better patient outcomes and thereby reduced care costs and higher profitability.

2.2.4.3. Complementarities of EHR with the two HIT Infrastructures

While the two-way complementarity of EHR with both AHIT and CHIT infrastructure may play a significant role on improved hospital performance, hospitals can obtain even greater benefits if EHR is fully integrated with AHIT and CHIT providing hospital-wide inter-connectivity. Prior work has noted that the integrated IT infrastructure enables firms to benefit from seamless connectivity and data exchange within and between units of a firm (e.g. Zhu and Kraemer 2002, Zhu 2004, Rai et al. 2006, Bharadwaj et al. 2007). The reason is that while the existing IT infrastructure expedites the deployment of business applications, the new business applications also help remove incompatibility of legacy systems and quickly and cost effectively respond to changes in business practices and strategies (Zhu and Kraemer 2002). Likewise, when a hospital's existing HIT infrastructure is flexible enough to accommodate the changes that EHR requires, the money and time for EHR implementation can be greatly reduced. At the same time, EHR can eliminate disconnected, isolated data and communication structure in the two HIT infrastructures, enable hospitals to simultaneously make better decisions on resource deployment and care plan, and to further conduct health research on their own patient population to improve hospital strategy (e.g. reducing hospital-introduced infections, Cerner 2012). This integrated HIT infrastructure therefore enable hospitals to improve internal connectivity and maintain business and clinical efficiency.

The enhanced interconnectivity within the hospital also enables them to coordinate and share information with other healthcare organizations both locally and nationally. The

HITECH Act (2009) mandates information sharing among hospitals via participation in health information exchanges (HIE) for hospitals to receive financial incentives from the U.S. government. While in its infancy, hospitals with fully integrated HIT infrastructure can benefit from shared patient information from other hospitals when admitting patients outside their affiliated health systems (McCarthy et al. 2009). Therefore, an integrated HIT system can allow hospitals to benefit from both internal and external connectivity and thereby improve overall performance. In the next section, we proceed to empirically test the suggested complementarities among EHR, AHIT, and CHIT infrastructure.

2.3. Methods

2.3.1. Data and Measures

We triangulated detailed HIT adoption and implementation data with hospital performance data collected from hospitals in California (CA) from 2002-2010. Our measures of the three HIT variables, namely AHIT, CHIT and EHR variables were drawn from an annual survey of U.S. hospitals conducted by the Healthcare Information and Management Systems Society (HIMSS). This nation-wide annual HIT survey which has been widely used in past studies and highly regarded for its reliability, contains data on various types of HIT systems that has been implemented in U.S. hospitals along with the current status of system automation (e.g. Furukawa et al. 2010, Angst et al. 2012, Dranove et al. 2012). The three measures of hospital performance data (see section 3.1.2) were obtained from the annual hospital financial and utilization data provided by the Office of Statewide Health Planning and Development (OSHPD). First, we used data on net patient revenue and operating expenses from hospital annual financial data which includes type of ownership (i.e. not-for-profit vs. for-profit), number of beds, net patient revenues, and operating expenses for all acute care hospitals licensed by the State of California. In addition, our measure of hospital discharge was obtained from the hospital utilization data. We matched the data from the three sources using the hospital's Medicare number as a unique key. The final sample comprises data from 246 unique hospitals over 9 years (2002-2010) for a panel of 2,217 hospital-years. (See Table 3 for the descriptive statistics).

Table 3. Descriptive Statistics

Variable	Mean	SD	Minimum	Maximum
Hospital Discharge (Count)	10255.8	7733.96	86	51071
Operating Expenses (US million$)	$35.89	$37.08	$29.8	$274.3
Patient Revenue (US million$)	$165.49	$198.73	$0.55	$1,904.15
AHIT (Count)	15.12	5.63	0	38
CHIT (Count)	10.16	9.3	0	37
Basic EHR (Count)	1.94	0.96	0	3
Advanced EHR (Count)	0.11	0.38	0	2
Teaching Status	0.07	0.25	0	1
Hospital Size (# Staffed Beds)	206.32	149.09	2	931
Hospital Age	38.11	33.08	0	156
Revenue from Medicare (%)	17.68	20.11	0	67.1
Health Service Area	8.58	3.88	1	14
In-Hospital System	0.83	0.38	0	1
Transfer-adjusted CMI	1.41	0.23	0.87	2.36
Urban	0.35	0.48	0	1
Hospital Ownership	5.32	2.34	0	9
Population Category	3.34	1.12	1	5
Physicians' EHR use in a County	0.34	0.1	0.02	0.68
Number of Physicians in a County	8.01	1.55	3.36	9.91

2.3.2. HIT Variables

Following the extant literature on the categorization of HIT in healthcare (e.g. Menon et al. 2009, Angst et al. 2010, and Angst et al. 2012), our measures of AHIT infrastructure and CHIT infrastructure were operationalized by the total respective counts of HIT applications used in the administrative and clinical functions. We identified common sets of HIT applications in both administrative units and clinical units which can be applicable to a wide variety of hospitals. While there are yearly variations in HIT applications in terms of its name and automation status in the HIMSS data throughout 2002-2010, the applications that have been consistently traced over nine years were subject to our operationalization of HIT infrastructure constructs. AHIT infrastructure variable was operationalized by the total number of HIT systems that are coded as "live and operational" or "automated" across the broader categories of financial management, financial decision support, revenue cycle management, and human resource. CHIT infrastructure variable included the total count of systems in the categories of health information management, laboratory, nursing, operating room, and radiology systems (HIMSS 2011). On average, hospitals in our sample had implemented about 15 applications in AHIT infrastructure and 10 applications in CHIT infrastructure.

In line with Dranove et al. (2012), we viewed EHR holistically as well as dimensionally. The overall EHR capability was operationalized by the total count of each "live and operational" or "automated" EHR system including clinical data repository (CDR), clinical decision support systems (CDSS), order entry (OE), computerized practitioner order entry (CPOE), and physician documentation (PD). Next, the dimensional EHR measures are defined by basic vs. advanced EHR- basic category of EHR includes CDR, CDSS, and OE whereas advanced category of EHR contains CPOE and PD as shown in Table 4. We counted the total number of basic EHR systems as well as advanced EHR systems that a single hospital has implemented. Our data reveal a great deal of variation in the adoption rates between basic and advanced EHR such that whereas 64 percent of hospitals in the sample have implemented basic EHR applications, only 5.5 percent of hospitals have implemented advanced EHR applications.

Table 4. Definition of Electronic Health Records (EHR)

EHR Functionalities	Definition
Clinical Data Repository (CDR)	A centralized database that allows organizations to collect, store, access and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization that provides healthcare organizations an open environment for accessing/viewing, managing, and reporting enterprise information
Clinical Decision Support (CDSS)	An application that uses pre-established rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions
Order Entry	Older version of CPOE with less integrated with CDSS
Computerized Practitioner Order Entry (CPOE)	An application that is designed to assist practitioners in creating and managing medical orders for patient services or medications (e.g. special electronic signature, workflow, and rules engine functions)
Physician Documentation	An application that allows clinicians to chart treatment, therapy and vital sign results for a patient (e.g. flow sheets and care plan documentation for a patient's course of therapy)

(Adopted from HIMSS Annual Reports 2011)

2.3.3. Dependent Variables

In HIT research, multidimensional measures of hospital performance have been utilized, including, measures of profitability, productivity, efficiency, and quality (Devaraj and Kohli 2003, Borzekowski 2009, Dranove et al. 2012, Kohli et al. 2013, Menon et al. 2000, Menon et al. 2009, Lee et al. 2012, Angst et al. 2012, Bardhan and Thouin 2013, Kohli et al. 2012, McCullough et al. 2013, Devaraj et al. 2013). In this study, we used three measures of hospital performance- *hospital discharge* as a productivity measure and *net patient revenue* and *operating expenses* as two accounting performance measures generated from the OSHPD dataset. Hospital discharge is defined as the formal release of an admitted inpatient from the hospital, including deaths and transfer of an inpatient from one type of care to another type of care within the hospital (OSHPD). This measure is operationalized as the total number of inpatient discharges from the hospital and serves as a strong proxy measure of the hospital's service volume. A large number of hospital discharges indicates that hospitals can efficiently admit and release more patients with their limited sets of beds, medical technologies, and clinical staffs in the geographic location (Morrisey et al. 1988). Thus, hospital discharge measure can capture the level of hospital service volume based on the regional patient mix. Second, as a profitability measure, we used the data on net patient revenue as the dollar amount received or expected to be received from third-party payers (insurers) and patients for hospital services rendered including the payments received for routine nursing care, emergency services, surgery services, lab tests, etc. Net patient revenue is a consistent measure of the current level of hospital services taking into account the reimbursement structure and market competition (Devaraj et al. 2013). Lastly, operating expenses are all the expenses associated with operating the hospital, such as salaries, employee benefits, purchased services, supplies, professional fees, depreciation, rentals, interest, and insurance which is a more general accounting measure of a hospital's overall cost performance. The average hospital in our sample had about 10,256 inpatient discharge, $165 million in net patient revenue and $36 million in operating costs.

2.3.4. Control Variables

Consistent with prior work in healthcare research (Vogel et al. 1993, Burns and Wholey 1991, RAND 2005), we included a number of control variables at the hospital and county level that are known to affect hospital performance. First, at hospital level, hospital performance may be affected by organizational characteristics including hospital age, hospital size, a hospital's teaching status, ownership structure, geographic location, in-system network affiliation, and case mix index (Angst et al. 2012). The age (in years) and size of the hospitals are considered to be important factors in healthcare research because newer and larger facilities might have better performance due to their access to capital and other complementary organizational resources. In our study, we used a control variable for hospital size measured by the number of staffed beds. As a hospital's ownership structure dictate inherently different organizational goals (e.g., not-for-profit vs. for-profit hospitals) and target different types of patient population, this affects overall hospital behaviors and relevant performance. So, we included nine categories of hospital ownership structure which are measured by categorical variables (1: city and/or county 2: district, 3: investor-corporation, 4: investor-partnership, 5: investor-limited liability company, 6: investor-individual, 7: non-profit corporation (including church-related), 8: State, 9: University of California). In addition, the percentage of Medicare revenue in 2007 were included which captures the degree of care provided to the older and sicker patients, while case mix index is included to control for differences between hospitals in the severity mix of their patient populations (Robinson and Luft 1985). Moreover, teaching hospitals tend to attend more patients with severe conditions and these hospitals are known to adopt more advanced HIT systems (RAND 2005). To control for this effect, we included teaching status as coded by a dichotomous variable (1: teaching hospital, 0: otherwise). Membership in a multihospital system or chain may also provide an existing hospital with a cost advantage relative to a potential freestanding hospital (Santerre and Neun 2010). In our study, hospitals' membership in two or more hospitals that are owned, leased, sponsored, or managed by a single corporate entity is operationalized as a binary variable (1: hospital network membership, 0: otherwise). Finally, a control for geographic location was included to indicate whether the hospital is located in an urban or rural area (1: urban, 0: rural).

Next, we used county level controls to account for geographical and regional confounding factors that affect hospital performance including population density, health service area, the number of healthcare providers in, and physicians' use of EHR in a county. The reason for including county level controls is because we consider a county to be the geographic boundary of a hospital (Robinson & Luft 1987) and operationalize several county-based local characteristics as control variables that affect the focal hospital's performance. First, we included population density in a county which is measured by a multinomial variable in order to control for the heterogeneity of patient population with various health conditions. In our sample, 42.18% of hospitals provide clinical services in counties with over 100K population size. Health service area (HSA) is measured by categorical variables indicating whether effective planning and development of health services are applied in that region (Morrisey et al. 1988). Furthermore, we controlled the total number of healthcare providers as a proxy for healthcare service intensity and physicians' use of EHR in a county as a proxy for HIT intensity in the location so that the performance impacts of EHR in a hospital can be efficiently captured in the local healthcare market.

2.4. Model Specification and Identification

In order to test the complementarity relationships between AHIT, CHIT infrastructure and EHR, we employed two types of statistical tests which have been widely used by multiple disciplines - measuring both correlations among key complementary variables of interest as well as performance differences that are driven by the complementarity relationships (e.g. Athey and Stern 1998, Aral and Weil 2007, Aral et al. 2012, Tambe et al. 2012). More specifically, in our study, the correlation tests investigates whether the three HIT variables are more likely to be adopted and implemented together by the focal hospital. The second test of performance differences indicates whether the complementary systems of three HIT variables lead to better hospital performance (Milgrom and Roberts 1990, Aral et al. 2012). We anticipate that the correlations among the two HIT infrastructures and EHR can form a system of complementarities which positively influence hospital performance.

$$\begin{aligned}
&\textit{Log}\text{ (Hospital Performance)} \\
&= \beta_0 + \beta_1 \text{ AHIT} + \beta_2 \text{ CHIT} + \beta_3 \text{ EHR} + \beta_4 \text{ AHIT} \times \text{EHR} \\
&\quad + \beta_5 \text{ CHIT} \times \text{EHR} + \beta_6 \text{ AHIT} \times \text{CHIT} + \beta_7 \text{ AHIT} \times \text{EHR} \times \text{CHIT} \\
&\quad + \textstyle\sum_j \beta_j \, Hospital\ Controls_j + \sum_k \beta_k \, County\ Controls_k \; + \; \varepsilon
\end{aligned}$$

Our final sample consists of multiple source of observational data in California State. It is often argued that causal claims are questionable due to non-randomly assigned variables of interest from observational data (Winship and Morgan 1999, Mithas and Krishnan 2008). Of particular concern is the fact that a hospital's propensity to adopt EHR systems may be endogenously determined. To account for this potential endogeneity, we divided our hospitals into two groups such that hospitals with scores above the mean on the sum of the three HIT variables (AHIT and CHIT infrastructures and EHR) were coded as one and hospitals that were below the mean were coded as zero (Heckman 1979, Bhardwaj et al. 2007). Then using Heckman two-step selection model, we first estimated probit model to assess the effects of organizational characteristics and regional characteristics, all of which were expected to influence a hospital's decision to adopt EHR in the location (RAND 2005). In the second stage, we then estimated our complementarities model by including inverse Mill's ratio from the first stage as a predictor variable.

Next, we attempted to rule out potential effects of omitted variable bias and unobserved heterogeneity that might simultaneously drive the adoption of EHR, AHIT and CHIT infrastructure, and hospital performance. To mitigate such biases, we employed panel regression with fixed effects, between-effects and random effects specification which account for any time-invariant heterogeneity that influence the complementarities relationship among AHIT, CHIT and EHR systems in a hospital context.

In addition to the Heckman two step regression and panel regression techniques, we further attempted to rule out spatial effects due to the location where a hospital resides in. Since we assume that hospital locations are quasi-fixed, patient populations in a given location can differ greatly from its neighboring location, in terms of volume, health conditions, and socio-economic status (SES). The flow of the shared patients from one hospital to the neighboring hospitals in the locale can be reasons that (1) hospitals' patient-related performance are likely to be correlated and (2) the selective adoption and implementation of HIT applications can be observed due to dominant medical symptoms of the patient population (RAND 2005). The location-based interactions among hospitals are often unobservable but it simultaneously influences a hospital's behaviors and performance in the location, which can be another source of potential endogeneity. The aforementioned regional interaction is called as *spatial dependence* or the coincidence of value similarity among neighboring observations in the location (Anselin 1988) and we attempt to control for this effect in order to obtain better estimates using spatial statistics. As a first step, we tested the residuals of the three dependent variables to determine whether there was a spatial dependence in the data by global Moran's I & Geary's C statistics (Hubert et al. 1981), which explain how related the values of one variable are based on the locations. In our data, Moran's I and Geary's C rejected the null hypothesis meaning that there was spatial dependence in the dataset ($p<0.0001$). Graphically, hospital discharges clearly demonstrated a pattern of spatial clustering as shown in Figure 2 and these patterns were similar for the other two dependent variables, net patient revenue and operating expenses. Additionally, we visualized this spatial clustering in a map as shown in Figure 3 which represented the regional variation of patient volume in the counties of California.

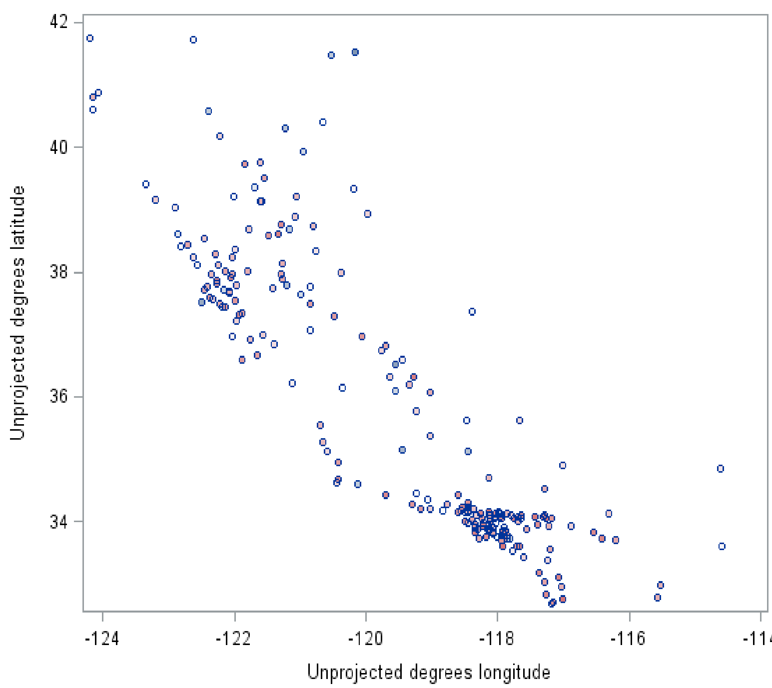

Figure 2. Spatial Distribution of Hospital Discharge

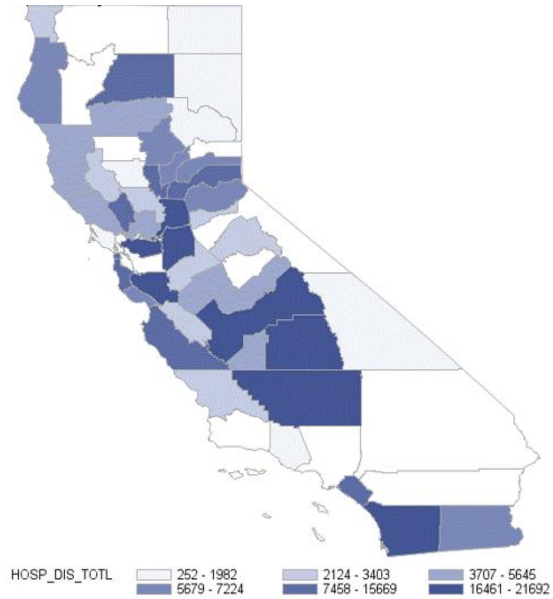

Figure 3. Regional Variation of Hospital Discharge in California Counties

From both spatial autocorrelation patterns and geographical representation above, our data clearly confirmed the existence of regional clustering patterns, and therefore the violation of homoskedasticiy assumption gave a valid reason to utilize spatial statistics beyond traditional ordinary least squares (OLS) estimation techniques. Among spatial estimation techniques, of our focus, spatial error model (SEM) posits that the spatial dependence can somehow be indirectly related to location and distance (Anselin et al. 2008) and treat the spatial correlation as a nuisance (Ward and Gleditsch 2008). In other words, instead of letting a hospital's performance y_i in the location *i* directly affect neighboring hospital's performance y_j in the location *j* which is too stringent, our model allows spatial correlation between two choice observations in two locations *i* and *j*. If their errors are correlated then the corresponding performance y_i and y_j are also correlated. Furthermore, it also suggests that such spatial correlation can be modeled by spatial weights or by geostatistical covariance structures (Ward and Gleditsch 2008). In our paper, we defined a regional covariance structure to model the indirect and unobserved spatial dependence based on geographic distance among regional hospitals. Using the spherical covariance functional form based on the empirical semivariogram results, we incorporate the covariance structure into the error term and fit the cross-section spatial error model.

2.5. Results

Table 5 shows pair-wise correlations between variables employed in this study. We found that our three dependent variables were highly correlated with one another. However as each dependent variable was tested in the separate models, it was not a matter of concern. In addition, the correlation coefficient between EHR variable and AHIT variable was 0.252 ($p<0.05$) and that with CHIT variable was 0.483 ($p<0.05$). These correlations supported the argument that EHR, AHIT and CHIT infrastructure are complements whilst not perfectly collinear.

2.5.1. The Correlation Test

Following Aral et al. (2012)'s suggestions, we first examined the evidence for three-way correlations between the two levels of EHR (basic vs. advanced) and the two HIT infrastructure variables after standardizing all the variables (subtracting the mean and then scaling by the standard deviation). To test three-way correlational relationships, we created binary variables for all three HIT variables by median split and then performed the three-way correlation tests. Table 6 show the summary of pair-wise correlations, after controlling for hospital age, size, teaching status, hospital ownership, urban/rural location, hospital in-system affiliation, transfer-adjusted case mix index (CMI), revenue from Medicare, and yearly trends. We found that the basic EHR functionalities comprising clinical data repository (CDR), clinical decision support (CDSS), and order entry, form a complementary system with the hospital's existing AHIT and CHIT infrastructures respectively. However, in hospitals with weaker clinical infrastructures (CHIT ≤ 0), the correlation between EHR and AHIT is negative and significant (β= -0.442), suggesting that lacking a strong CHIT component, hospitals were unable to leverage the EHR capability simply via the AHIT infrastructure. It is also interesting to note that advanced EHR capabilities did not reveal any significant correlations with either AHIT or CHIT components, suggesting that hospitals may still be too early in the implementation cycle of EHR to benefit from the more advanced capabilities embedded in EHR. Taken together, the patterns of correlations is consistent with our expectation that three-way complementarities among basic EHR, AHIT and CHIT must be examined together to understand the performance implications of these systems of technologies.

Table 5. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	**Hospital Discharge**																		
2	**Net Patient Revenue**	0.803*																	
3	**Operating Expenses**	0.823*	0.948*																
4	**EHR**	0.147*	0.067*	0.075*															
5	**AHIT**	0.139*	0.206*	0.210*	0.252*														
6	**CHIT**	0.163*	0.260*	0.214*	0.483*	0.597*													
7	**Teaching Status**	0.394*	0.593*	0.587*	0.030	0.069*	0.121*												
8	**Hospital Size**	0.819*	0.814*	0.847*	0.091*	0.228*	0.163*	0.470*											
9	**Hospital Age**	0.250*	0.168*	0.188*	0.021	-0.169*	-0.082*	0.125*	0.188*										
10	**Revenue from Medicare**	-0.128*	-0.199*	-0.221*	-0.032	-0.092*	-0.055	-0.185*	-0.175*	-0.058									
11	**Case Mix Index (CMI)**	0.518*	0.542*	0.527*	0.019	0.200*	0.154*	0.242*	0.497*	-0.034	-0.040								
12	**Population Category**	0.224*	0.168*	0.211*	-0.017	-0.065*	0.074*	0.125*	0.248*	0.101*	-0.036	0.165*							
13	**Health Service Area**	0.195*	-0.037	-0.015	-0.024	0.047*	0.030	-0.013	0.108*	0.064*	0.018	-0.041	0.157*						
14	**Hospital In-network**	0.012	0.014	0.030	-0.013	-0.079*	-0.156*	0.017	0.005	-0.362*	0.076*	0.135*	0.019	-0.137*					
15	**% Physician using EHR**	-0.018	0.041	0.013	0.087*	0.136*	-0.007	-0.054*	-0.026	-0.048*	-0.102*	0.075*	-0.262*	-0.218*	0.081*				
16	**# Physicians in a county**	0.328*	0.163*	0.216*	0.014	0.081*	0.054	0.135*	0.329*	0.056*	0.111*	0.133*	0.262*	0.612*	0.043*	-0.317*			
17	**Urban**	-0.144*	-0.071*	-0.089*	-0.050*	-0.013	-0.060*	-0.068*	-0.166*	-0.100*	-0.168*	0.002	-0.134*	-0.387*	0.088*	0.371*	-0.595*		
18	**Hospital Ownership**	0.182*	0.193*	0.131*	0.063*	-0.067*	-0.019	-0.048*	0.174*	-0.139*	-0.004	0.270*	0.090*	-0.210*	0.156*	0.045*	-0.027	0.100*	
19	**Year**	0.034	0.183*	0.218*	0.003	-0.004	-0.005	0.073*	-0.012	0.031	-0.007	0.012	0.016	-0.006	-0.014	0.008	0.002	0.009	0.025

* Denote significance at $p<0.05$

Table 6. Summary of Three-Way Correlations Test

	All Obs.	AHIT>Median	AHIT ≤ Median
	DV: Basic EHR (binary)		
CHIT	0.448*** (0.031)	0.577*** (0.075)	0.55*** (0.058)

	All Obs.	AHIT>Median	AHIT ≤ Median
	DV: Advanced EHR (binary)		
CHIT	-0.046 (0.027)	0.096 (0.061)	0.043 (0.051)

	All Obs.	CHIT>Median	CHIT ≤ Median
	DV: Basic EHR (binary)		
AHIT	0.219*** (0.001)	0.282*** (0.004)	0.078*** (0.003)

	All Obs.	CHIT>Median	CHIT ≤ Median
	DV: Advanced EHR (binary)		
AHIT	0.024*** (0.002)	-0.053*** (0.003)	0.177*** (0.006)

Notes. Parameter estimates of logistic regression analysis are shown. Hospital clustered standard errors are shown in parentheses. EHR basic consists of CDR, CDSS, and order entry while CPOE and physician document comprise EHR advance. *p<0.01, **p<0.05, ***p<0.001.

2.5.2. The Performance Test

Table 7 to Table 9 show the associations among the three measures of dependent variables and complementarities between AHIT×EHR, CHIT×EHR as well as three way interactions of all three variables. In each table, the estimates in columns (1) to (4) were derived from the spatial error model (SEM) regressions with maximum likelihood estimation (MLE) to provide robust estimates in the presence of spatial dependence. First, in column (1), we established a baseline estimate of the contribution of EHR to the respective performance measure. The coefficient estimate of EHR was positive and significant for all measures - hospital discharge ($\beta=0.035$, $p<0.01$), net patient revenue ($\beta=0.045$, $p<0.01$) and on operating expenses ($\beta=0.069$, $p<0.0001$). These results indicate that while the investments in EHR increase overall levels of hospital expenses (Table 9 – column 1), they also contribute to the hospital's ability to increase net revenues (Table 8 – Column 1), possibly through better tracking of the services rendered and thereby allowing for a greater percentage of insurance claims to be settled quickly, and also by driving greater patient volumes with improved throughput (Table 7 – Column 1). In column (2) and column (3), we selectively include one of the HIT infrastructure measures, either AHIT or CHIT and its interaction term with EHR. In column (2), although the coefficient estimate of AHIT infrastructure was positive and significant across three performance measures, the interaction term between AHIT and EHR was either negatively significant (Table 7) or insignificant (Table 8 and Table 9). On the other hand, the interaction effects of EHR with CHIT infrastructure were positive and statistically significant on net patient revenue (Table 8) and operating expenses (Table 9) in column (3). In column (4), we included all combinations of two-way interaction terms and also included the three-way interaction term, capturing the interactions among AHIT, CHIT, and EHR. In the main results of SEM, reported in column (4), the coefficient estimates on two-way interaction term of AHIT×EHR were positive and significant on net patient revenue ($\beta=0.068$, $p<0.1$) and two-way interaction term of CHIT×EHR was positive and significant on hospital discharge ($\beta=0.064$, $p<0.05$), whereas the three-way interaction term was positive and significant only on hospital discharge ($\beta=0.068$, $p<0.01$).

The SEM results are also compared with Heckman selection model in column (5), the pooled OLS regression with cluster in column (6), and panel regression with between effects in column (7) and random effects specification in column (8). The results from non-SEM techniques similarly indicate that the two-way complements of CHIT×EHR was positively associated with increase in hospital discharge and reduction in operating expenses whereas AHIT×EHR appeared to enhance net patient revenue. In the non-SEM results, the complementary impacts of AHIT×EHR and CHIT×EHR seesawed across hospital performance. Namely, the impacts of AHIT×EHR enhance a hospital's patient-related revenue while concurrently increasing overall costs of hospital operation of the focal hospital. Likewise, the complementarities of CHIT×EHR negatively impact net patient revenue whereas it helps hospitals to positively reduce cost of care. One possible explanation for these results are that a hospital's profit increase can come from revenue expansion initiative, cost reduction initiative or both simultaneously (cf. Rust et al. 2002). However, for a hospital with dual governing structures with respect to its performance goals, pricing strategies, and IT capability in administrative units and clinical units, these differences can drive differential complementarity benefits on overall hospital performance metrics.

Together, these estimates provide the evidence for complementarities between EHR and the two HIT infrastructures such that the value of EHR increases when either or both AHIT and CHIT infrastructure are matched with the functionalities of EHR.

2.5.3. Robustness Checks

While spatial error model (SEM) can be useful for ruling out biases owing to spatially omitted variables (Bradlow et al. 2005), in an attempt to further validate our results, we also used an outcome-based approach to test the robustness of the results obtained as it can be used to effectively address any remaining selection bias. In observational data, causal claim of a treatment effect (i.e. the adoption of EHR in our study) cannot be conclusively determined as we do not observe whether such complementarities comes from the HIT per se or perhaps from other unobserved organizational characteristics, that are not included in the research models. Hence, we utilized propensity scores matching technique by locating different groups based on the propensity score, which was calculated as the probability that a hospital will be assigned to a condition or treatment group based on the hospital size, age, and the level of existing AHIT and CHIT infrastructures. We defined EHR treatment group when hospitals have implemented both basic and advanced EHR systems whereas control groups have only implemented the basic EHR systems[2]. As shown in Figure 4, we stratified our sample based on calculated propensity score and identified five strata of hospitals with similar characteristics.[3] Then, we re-ran our SEM model in comparison with treatment and control groups in block 3 with similar number of control and treatment observations. Our results in showed that the two-way complementarities of EHR×CHIT reduce operating expenses and three-way complementarities of AHIT, CHIT, and EHR increase net patient revenue in treatment group (n=30) ($p<0.05$). Interestingly, the positive effect of three-way complementarities on hospital discharge was found in control group of hospitals which have

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[2] As the adoption rate of basic EHR was 64% in our sample, we view the adoption of advanced EHR as an indicator of HIT intensity of a hospital.

[3] We used stratification as conditioning method to estimate the average treatment effects on the treated (ATT). Clearly, t test results suggested that there are group mean difference between treatment and control groups along our three models of dependent variables ($p<0.05$).

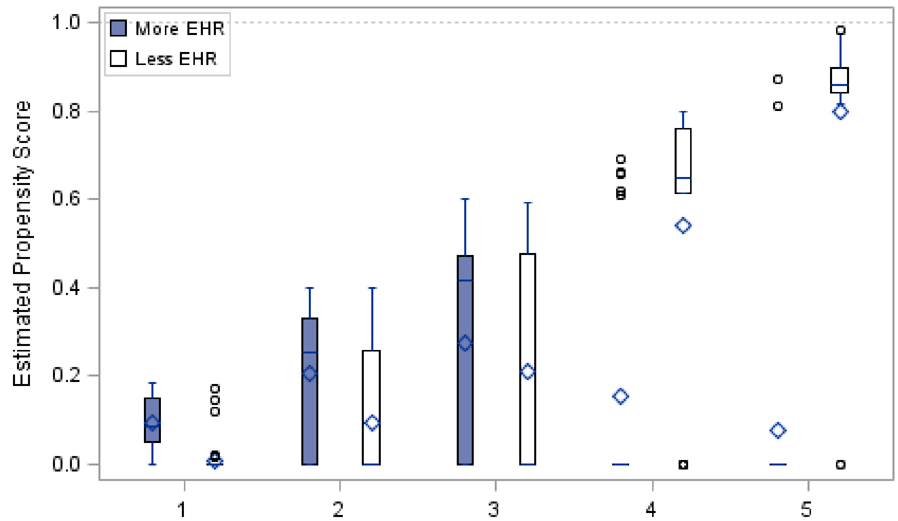


Figure 4. Box Plot of Propensity Score Distribution across Strata

implemented basic sets of EHR applications. These results therefore reaffirmed that while three-way complementarities of basic EHR and the two HIT infrastructures can increase a hospitals' patient volume in the location, only HIT intensive hospitals with advanced EHR can translate such increased service volume into net patient revenue. We further discuss the results in the following section.

Table 7. Complementarities between EHR and HIT infrastructure on Hospital Discharge

	Log (Hospital Discharge)							
	SEM				Heckman	Cluster	Panel BE	Panel RE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	4.795***	4.955***	5.316***	5.461***	9.721***	2.746***	2.678***	0.857
	(0.124)	(0.123)	(0.196)	(0.197)	(0.220)	(0.562)	(0.694)	(0.755)
EHR	0.035***	-0.011	-0.077***	-0.132***	-0.304***	0.324*	2.095	-0.309
	(0.012)	(0.012)	(0.022)	(0.025)	(0.118)	(0.193)	(3.208)	(0.366)
AHIT		0.092***		0.020	0.070	0.021	0.014	0.192**
		(0.014)		(0.028)	(0.066)	(0.072)	(0.088)	(0.093)
EHR×AHIT		-0.059***		0.037	-0.121*	-0.005	0.050	0.023
		(0.010)		(0.025)	(0.070)	(0.053)	(0.091)	(0.096)
CHIT			0.027	0.049**	0.032	0.042	0.026	0.061
			(0.019)	(0.025)	(0.085)	(0.086)	(0.104)	(0.118)
EHR× CHIT			0.002	0.064**	0.283***	0.166**	0.224	0.254**
			(0.016)	(0.027)	(0.084)	(0.073)	(0.116)	(0.131)
AHIT×CHIT				-0.156***	0.060	-0.035	-0.120	-0.052
				(0.033)	(0.083)	(0.061)	(0.109)	(0.122)
AHIT×CHIT×EHR				0.063***	-0.054	0.005	0.019	0.010
				(0.017)	(0.049)	(0.030)	(0.059)	(0.066)
N	1007	967	579	579	1607	1607	1607	1607
R-Square						0.37	0.33	0.24
- 2 LL	1358.3	1213.3	747.8	725.4				
AIC	1406.3	1265.3	799.8	785.4				
BIC	1543.1	1413.6	948.1	956.5				

***Significant at p<0.01; **Significant at p<0.05; *Significant at p<0.1. Spatially robust standard errors are shown in parentheses in column (1) through (4). Panel regression models reported in column (8) and (9) include EHR lag variables at t-1 and t-3 to account for a hospital's EHR learning effects. A model of hospital discharge is adjusted by hospital-level length of stay.

Table 8. Complementarities between EHR and HIT infrastructure on Net Patient Revenue

	Log (Net Patient Revenue)							
	SEM				Heckman	Cluster	Panel BE	Panel RE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	14.012***	13.881***	13.706***	13.703***	21.047***	18.153***	18.118***	18.877***
	(0.166)	(0.174)	(0.268)	(0.270)	(0.579)	(2.722)	(2.774)	(2.392)
EHR	0.045***	0.007	0.072**	0.036	-3.494***	-0.883	-9.336	-0.881***
	(0.018)	(0.019)	(0.033)	(0.038)	(0.312)	(1.705)	(13.076)	(0.332)
AHIT		0.079***		0.129***	1.250***	1.138***	1.196***	1.082***
		(0.022)		(0.044)	(0.171)	(0.355)	(0.361)	(0.221)
EHR×AHIT		0.011		0.068*	2.672***	1.410	1.538***	0.145
		(0.016)		(0.039)	(0.183)	(0.365)	(0.369)	(0.159)
CHIT			0.043	-0.009	0.095	-0.642*	-0.693*	-0.851**
			(0.030)	(0.039)	(0.219)	(0.330)	(0.425)	(0.422)
EHR× CHIT			0.070***	0.047	-1.426***	-0.716	-0.829*	-0.713
			(0.024)	(0.041)	(0.220)	(0.489)	(0.471)	(0.459)
AHIT×CHIT				-0.060	-0.549***	-0.306	-0.234	0.461
				(0.050)	(0.214)	(0.291)	(0.446)	(0.431)
AHIT×CHIT×EHR				0.014	-0.069	-0.115	-0.164	-0.124
				(0.026)	(0.127)	(0.131)	(0.240)	(0.235)
N	1011	970	581	581	1607	1607	1607	1607
R-Square						0.31	0.30	0.22
- 2 LL	1493.5	1376.7	856.1	837.5				
AIC	1541.5	1428.7	908.1	897.5				
BIC	1678.4	1577	1056.4	1068.6				

***Significant at p<0.01; **Significant at p<0.05; *Significant at p<0.1. Spatially robust standard errors are shown in parentheses in column (1) through (4). Panel regression models reported in column (8) and (9) include EHR lag variables at t-1 and t-3 to account for a hospital's EHR learning effects. A model of hospital discharge is adjusted by hospital-level length of stay.

Table 9. Complementarities between EHR and HIT infrastructure on Operating Expenses

	Log (Operating Expenses)							
	SEM				Heckman	Cluster	Panel BE	Panel RE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	11.496***	11.449***	11.545***	11.591***	19.300***	15.337***	15.430***	15.556***
	(0.137)	(0.146)	(0.218)	(0.222)	(0.535)	(2.511)	(2.521)	(2.311)
EHR	0.069***	0.043***	0.054**	0.023	-3.221***	-0.697	-7.695	-0.514
	(0.015)	(0.016)	(0.027)	(0.031)	(0.288)	(1.481)	(11.882)	(0.445)
AHIT		0.073***		0.019	1.147***	1.056***	1.114***	0.993***
		(0.018)		(0.036)	(0.158)	(0.321)	(0.328)	(0.230)
EHR×AHIT		-0.011		0.060	2.410***	1.299***	1.421***	0.401*
		(0.013)		(0.032)	(0.169)	(0.330)	(0.335)	(0.206)
CHIT			0.061**	0.065**	0.142	-0.582*	-0.628*	-0.738*
			(0.024)	(0.032)	(0.201)	(0.303)	(0.387)	(0.385)
EHR× CHIT			0.051***	0.043	-1.351***	-0.663	-0.766*	-0.716*
			(0.019)	(0.034)	(0.203)	(0.452)	(0.428)	(0.421)
AHIT×CHIT				-0.066*	-0.538***	-0.289	-0.231	0.325
				(0.041)	(0.197)	(0.273)	(0.405)	(0.394)
AHIT×CHIT×EHR				0.023	-0.032	-0.102	-0.145	-0.110
				(0.021)	(0.117)	(0.124)	(0.218)	(0.214)
N	1011	970	581	581	1607	1607	1607	1607
R-Square						0.31	0.30	0.23
- 2 LL	1105.6	1035.2	613.5	607.6				
AIC	1153.6	1087.2	665.5	667.6				
BIC	1290.5	1235.5	813.8	838.7				

***Significant at p<0.01; **Significant at p<0.05; *Significant at p<0.1. Spatially robust standard errors are shown in parentheses in column (1) through (4). Panel regression models reported in column (8) and (9) include EHR lag variables at t-1 and t-3 to account for a hospital's EHR learning effects. A model of hospital discharge is adjusted by hospital-level length of stay.

2.6. Discussion

The findings suggest that the interactions between two types of extant HIT infrastructures and EHR have disproportionately contributed to hospital performance. EHR was found to be complementary to the existing AHIT infrastructure leading to increases in net patient revenues in the spatial analysis. With CHIT infrastructure, the complementary effect of EHR was seen in increasing patient discharge while reducing operating expenses. The three-way interactions of EHR with AHIT and CHIT improved hospital discharge rates, but only HIT intensive hospitals have the capability to manage such increased service volume and convert the higher volume to an increased revenue[4]. The main contribution of this paper is to explore the role of the existing HIT infrastructures as key enablers of EHR implementation in explaining variations in hospital performance. As noted earlier, prior literature has emphasized the importance of organizational and technological complements to explain performance impacts of EHR implementation (Dranove et al. 2012, McCullough et al. 2013). However, these studies have neither explicitly incorporated holistic measures of the existing CHIT infrastructure nor have they examined the role of the two distinct HIT infrastructures in conjunction with the new EHR implementations. Furthermore, our study takes into account the fact that EHR adoption and hospital performance are simultaneously impacted by regional (location-specific) factors and therefore, we incorporate spatial error models so as to explicitly control location based biases. By separating EHR from the CHIT infrastructure and including the interaction terms with the existing AHIT as well as CHIT infrastructure in the model, we find that inclusion of these HIT-related complements provide a more granular view on whether and how EHR contributes to performance gains.

[4] These mostly not-for-profit hospitals (76.67%) tend to be large, newer (17 years of hospital age), participating in hospital in-network (83.33%) with maintaining high level of AHIT and CHIT infrastructure capability in our propensity score matched sample.

Our results reveal differential performance impacts of a set of complementary HIT systems. First, in the model that uses hospital discharge as the dependent variable, the interaction effect estimates of CHIT infrastructure and EHR become salient, indicating that hospitals derive the maximum benefit from implementing EHR when these functionalities are adequately supported by the underlying CHIT infrastructure. The improved hospital care provision, and care coordination that are complemented by EHR and CHIT infrastructure allow hospitals to efficiently improve patient volume and increase the number of patient discharge. Second, the two-way complementary effects of EHR×AHIT infrastructure appears to enhance net patient revenue. Prior HIT literature has widely documented that administrative HIT infrastructure have direct impacts on productivity and financial performance of a hospital (Menachemi et al. 2006, Borzekowski 2009, Menon et al. 2009). In addition to its positive sole performance impacts of AHIT infrastructure, we found that the complementarities of AHIT infrastructure with EHR data can enable hospitals to better manage administrative patient care service and enhance net patient revenue in a hospital by EHR-driven electronic connectivity and access to such combined health data. Third, the two-way complementary effects of EHR×CHIT infrastructure is shown to reduce operating expenses when EHR lag variables (at t-1 and t-3) are included such that EHR adopter hospitals can reduce costs in drug, radiology and laboratory usage, reduced nursing time, fewer medical errors and shorter inpatient length of stay (Hillestad et al. 2005). This result is in line with prior literature that the HIT intensive hospitals are actually able to reduce hospital costs with the learning effects (Borzekowski 2009, Dranove et al. 2012). Finally, results indicating that the three-way complementarities of HIT with basic level of EHR increase service volume in hospitals but only HIT intensive hospitals where advanced EHR is implemented are capable of enhancing net patient revenue. We expect that the three-way complementary benefits arise at multiple levels of the HIT intensive hospitals. At the individual level, physicians and nurses have instant access to medical information and assistance for clinical decision making which can be leveraged for more effective care decisions (Huckman and Pisano 2006). At a group level, care teams can use the EHR systems to place clinical orders and produce accurate health information on patient diagnoses and treatments, especially as the patient moves across different clinical units. At the organization level, data from AHIT and CHIT infrastructure can be stored electronically such that hospital-wide integrated data management can improve the processes of administrative billing and claims, which require accuracy of the underlying health information.

A key contribution of this study is also the introduction of spatial statistics to model the impacts of EHR, thereby providing greater confidence that our results are not driven by endogeneity arising due to the location. Viewing a hospital in a given location as the unit of analysis, we identify a hospital's location specific characteristics as contextual factors that consistently affect the focal hospitals' behaviors in the market. Instead of entering the selective sets of location-based covariates into the complementary interactions, we identify and include unobserved and location-based spatial dependence among hospitals in the error term. In doing so, we are able to validate our complementary interaction results while effectively ruling out confounding effects that simultaneously affect both HIT implementation and hospital performance at a spatial context.

Before discussing managerial implications, we note some limitations of this research which can provide avenues for further research. First, we restricted our focus to the complementarity relationships between a subset of the two HIT infrastructures and electronic health records. Future research could extend our research model by incorporating more broad sets of HIT infrastructure measures including network, hardware, possibly cloud-based organizational platform and governance structure. Second, it would be useful to investigate the role of individual EHR functionality on hospital performance at more granular level. Since the term EHR applications have been variedly applied across healthcare organizations (Staggers et al. 2008), it is unclear whether the same EHR applications (e.g. CPOE) provide hospitals with the same functionalities. Although our study follows broad categorization of EHR by a reliable source (i.e. HIMSS Analytics) as well as established work (e.g. Dranove et al. 2012), the detailed information on EHR functionality would allow researchers to further investigate differential performance impacts of EHR. Third, while our dataset on California hospitals enables us to control for the potential regional confounding factors and serves as a basis for incorporating spatial error model, further research is needed to confirm generalizability of our findings by testing our model in other hospitals from other states. Fourth, although this model captures the current level of HIT investment and its leveraging capability in the hospitals, our data do not include intangible IT resources such as clinical process redesign, health knowledge management, and department wide coordination mechanisms. Future research can include some elements in hospital strategy, structure, or policy that efficiently complement the performance effects of EHR. Lastly, our dataset do not display mature adoption of advanced EHR systems such as CPOE and physician documentation. It would be fruitful to revisit our research model when more mature data of advanced EHR system becomes available.

Results from this study suggest that the inconsistent statistical findings about the relationship between EHR and hospital performance may be attributed to our incomplete understanding of the nature of EHR systems and the role of the existing HIT infrastructure within a hospital. In fact, EHR systems more become effective in the presence of complementary administrative and clinical HIT infrastructures, and therefore testing the main effects of EHR may not fully capture their performance effects. Our study also has several managerial implications. Healthcare policymakers and practitioners should put more emphasis on reassessing hospitals' current level of HIT infrastructure capability in order for hospitals to effectively deploy and operate the new EHR implementations. Clearly, investments in EHR cannot be seen as a panacea for poorly managed HIT infrastructure which are more likely to serve as a deterrent for successful EHR implementations. This finding also aligns well with empirical findings that amid rapidly growing adoption of EHR, it is still quite a challenge for them to establish and maintain the complementarity HIT capability that are matched with EHR (HIMSS 2012). Although the compatibility of the existing HIT infrastructure is the first step toward building EHR capability across various hospitals, there is little empirical evidence as to how such hospital specific HIT capability influences the value of EHR on hospital performance. We show here that EHR capabilities are harnessed by the hospitals' idiosyncratic, existing AHIT and CHIT infrastructure capability and the synergistic effects among them differentially lead to improved hospital performance. Thus, thorough reassessment of hospitals' HIT infrastructure capability prior to EHR deployment can provide appropriate plans for facilitating successful EHR implementations across hospitals (Broadbent et al. 1999).

2.7. Conclusions

Whether and how EHR contributes to hospital performance has been an enduring question in HIT research and practice. While the use of EHR has begun to accelerate in hospitals (HIMSS 212, Human and Health Services 2013), there has been little empirical evidence as to why hospitals disproportionately reap the benefits from EHR implementation. This renewed "productivity paradox" in the healthcare context, calls for attention to the heterogeneity in both health providers and technology (Agarwal et al. 2010) and therefore, there is an urgency to provide a snapshot of EHR impacts at the current level of HIT infrastructure and discuss further improvement from that starting points. At the intersection of IT business value and healthcare research, we developed a model that explained substantial hospital performance variance in the spatial sample of U.S. hospitals. This study explicitly models the relationships between HIT infrastructures and EHR in order to efficiently explain whether and how EHR create value to the investing hospitals. Subscribing to the view of a hospital as an entity with a loosely-coupled internal structure and externally unobserved correlations with neighboring hospitals in the location, our study proposes the relational view of EHR which distinguishes it from prior literature. The explicit interaction effects between EHR and a hospital's two distinct HIT infrastructures on hospital performance were examined, while simultaneously controlling for location-based confounding effects. We have found that the complementarities of the two HIT infrastructures and EHR were indeed sources of performance gains such that the impacts of EHR were greatly modified by both the two way complementarities of *ex ante* AHIT and CHIT infrastructure capability and three-way complementarities on selective measures of hospital performance. The results of this study can be a foundation to understand the systematic fit between EHR and the existing HIT infrastructures so that future research can refine the theory and measurement of HIT capability and hospital performance.

Chapter 3

Measuring the Impacts of Feature-based HIT on Individual Patients' Length of Stay

3.1. Introduction

The linkage between electronic health records (EHR) and clinical outcome has been an ongoing concern in HIT research. Although EHR are widely expected to improve quality and convenience of patient care, accuracy of diagnoses, and patient health outcomes (Department of Health and Human Services), the empirical evidences appear to contradict – positive relationships of EHR system with clinical outcome (Rind et al. 1994; Tierney et al. 1993; Shea et al. 1995) whereas null effects of EHR (Garg et al. 2005; McCullough et al. 2013). Since clinical outcome is resulted from the interactions of care tasks, the use of specific EHR technologies and heterogeneous patients in a care service dyad, the omission of such interactions may be the major reason of inconsistent results and therefore, investigation on these is a potent area of study that has possibilities for enhancing clinical outcome.

The purpose of this paper is to empirically examine a model of the linkage between task, technology, and patient by drawing on insights from two literature – feature centric view of IT and IT use in a hospital care context. The essence of this model is the assertion that feature use of EHR system creates difference in care service outcome through a fit between care tasks and information processing capability of EHR features including electronic clinical documentation, result viewing, computerized provider order entry, decision support, and bar coding (see table 10 for further explanation of each feature). This paper simultaneously examines all relevant system features on the same dependent variable so that it can provide a complementary view of how the features of the focal technology can create differential value and influence relevant performance disproportionately. To test the research model, we triangulate two major sources of archival data from the Office of Statewide Health Planning and Development (OSHPD) and from American Hospital Association's Electronic Health Records (EHR) adoption data over the three years (2008-2010). Our research model is estimated by Hierarchical Linear Modeling (HLM) as well with cross-section quantile regression. The findings suggest that the use of EHR features differentially helps hospitals cope with various care situations by allowing care providers to create, access, and retrieve real-time information as well as by streamlining communication processes. Moreover, while the value of EHR is transferred to the patients through features use in various care situations, the impacts of EHR features are also greatly modified by patient heterogeneity.

3.2. Theoretical Background

3.2.1. IT use

While the definitions of *IT use* vary, this study adopts the definition of *IT use* as an individual user's employment of system to perform a task (Burton-Jones and Straub 2006; Burton-Jones and Gallivan 2007). Prior IS research has conceptualized IT use as a contextual variable whose impacts differ at multilevel – individual level, group level and firm level. At individual or group level, measures of IT use are related to one or more feature use of a system while system use is defined as a multilevel construct based on function, structure, and context of system use at firm level (Burton-Jones and Gallivan 2007). Mechanisms on how IT use affects designed goals and performance have been explained by some notable theories including technology acceptance model (TAM) (Davis 1989), IS success model (DeLone and McLean 1992), task technology fit (Goodhue and Thompson 1995), absorptive structuration theory (AST, DeSantis and Poole 1994), and information processing theory (Galbraith 1973). The shared consensus among these theories are that there needs to be a cognitive (at individual level) or objective fit (at more firm level) between intended tasks and the technology use so as to improve various levels of performance. In most cases, tasks are uncertain, complex, or equivocal such that *IT use* of either form- feature use or collective use- can provide more information processing capability – the capability to gather, share, aggregate, structure, or evaluate information (Zigurs and Buckland 1998).

3.2.2. Feature Use of IT

Prior IS literature has conceptualized IT artifact (Orlikowski and Iacono 2001) at different levels of analysis (Sidorova et al. 2008). In their seminal paper, Orlikowski and Iacono (2001) define IT artifact as "bundles of material and cultural properties packaged in some socially recognizable form such as hardware and software" (p 121) and propose four dimensions of conceptualizing IT artifact in IS research - tool, proxy, ensemble and nominal view. Namely, IT is viewed as a computing resource to affect, alter, or transform various performances (*tool view*); as surrogate measures capturing the essential aspect, property or value of IT (*proxy view*); as a package relating to activities in a complex and dynamic social context (*ensemble view*); or as an implicit entity (*nominal view*). Such conceptualization of IT artifact becomes more variant when matched with different levels of analysis (i.e. individuals, groups, organizations, or markets) (Sidorova et al. 2008). On one hand, at organization or market levels, a technology is regarded as monolithic or a black box (Latour 1987) such that the number of applications indicate the level of technological innovation of a firm or an industry sector. For example, IT artifact is defined by the existence of a technology such as enterprise resource planning (ERP), customer relationship management (CRM), and supply chain management (SCM). On the other hand, at individual or group levels, feature centric view of technology is widely adopted and studied (Jarvenpaa et al. 1988; George et al. 1990; DeSanctis and Poole 1994; Orlikowski and Gash 1994; Griffith 1999; Dennis and Garfield 2003; Jasperson et al. 2005; Sun 2012; Leonardi 2013). A considerable focus is laid on the fact that IT application is consisted of "constructed convenient fictions for describing and discussing particular constellations of features" (p. 208, Griffith and Northcraft 1994). In fact, each feature is recognized by individuals and groups based on idiosyncratic interpretation (or frames, Orlikowski and Gash 1994) which triggers individual users to sense making of the technology (Griffith 1999) and select and revise the sets of feature in use (Sun 2012). In addition, such schema allows groups to perceive whether utilization of a certain feature fits with their given tasks (DeSanctis and Poole 1994; Jasperson et al 2005) or afford shared goals in the groups (Leonardi 2013). For example, while performing a task, an individual freely selects features of MS Word (e.g. track changes) that influence her work speed and efficiency (Sun 2012). At group level, visual representation of electronic blackboard system can enhance group communication (Jarvenppa et al. 1988). Therefore, it is fair to say that how IT features work is largely dependent on either individual's cognitive interpretation or objective fit between the task and the related system features (Goodhue and Thompson 1995).

Although the value of feature centric view of technology is well documented in the prior literature, there has been a criticism over feature-based definition of IT artifact. In particular, Markus and Silver (2008) argued that

> Feature lists are problematic, in part, because they do not focus attention on what is truly important about the technology… In addition, systems vary so much in the presentation of their features that information based on features alone makes it virtually impossible to compare systems or versions of systems (p. 333, DeSanctis et al. 1994) (p. 614).

In other words, some selective features cannot fully represent the entire technology and there are features within features with various versions, functionalities, and naming such that feature-level IT artifact may provide incomplete understanding of the technology. So-called "repeating decomposition problem" has redirected IS researchers to consider rather structural features instead of a pure list of features (DeSanctis and Poole 1995) or features and its functional and symbolic expressions together (Leonardi 2013). However, if the list of features reflect the final outputs of technology (e.g. documents, drawing, transcripts and representations) and can be recognizable across organizational units, then the aforementioned "repeating decomposition problem" may not be of a concern (Markus and Silver 2008).

For this reason, feature-based IT artifact has been widely used in qualitative research method when compared to the positivistic research. For instance, the use of electronic medical records by clinical care teams in a hospital (Oborn et al. 2011) or feature use of a manufacturing simulation technology (Leonardi 2013) were illustrated by interpretative research. It is true that such interpretative research has provided in-depth understanding of system feature impacts, there is also a theoretical implication. In such research, objective investigation into whether such features support intended tasks and improve local performance is not fleshed out because social actors' cognition and perception on the features are intermeshed (Orlikowski and Baroudi 1991). Taken together, positivistic view or variance theory can also inform us impartial viewpoint on objective fit between intended tasks or task attributes and focal features.

3.2.3. Feature-centric IT artifact: The Feature Use of EHR

By linking this two streams of research, we define the feature use of EHR as a user's employment of EHR features to perform various care tasks and propose that the information processing capability of each feature of EHR can differentially influence task outcome. As shown in Table 10, each feature reflects the final outputs of technology such as patient demographics and lab reports and can be recognizable across clinical units of a hospital, this paper can examine the performance impacts of EHR feature use without the repeating decomposition problem in positivistic theoretical lens.

Table 10. Items for the EHR Feature Use Measure

EHR Functionality	Formative Measure Items	Reflective Measure Items
Electronic Clinical Documentation (ECD)	• Patient Demographics • Physician notes • Nursing assessments • Problem lists • Medication lists • Discharge summaries • Advanced directives	• Nursing assessments • Problem lists
Result Viewing (RV)	• Lab reports • Radiology reports • Radiology images • Diagnostic test results • Diagnostic test images • Consultant reports	• Lab reports • Radiology reports
Bar Coding (BC)	• Laboratory specimens • Tracking pharmaceuticals • Pharmaceutical administration • Supply chain management • Patient ID	• Laboratory specimens • Tracking pharmaceuticals • Pharmaceutical administration • Supply chain management • Patient ID
Computerized Provider Order Entry (CPOE)	• Laboratory tests • Radiology tests • Medications • Consultation requests	• Laboratory tests • Radiology tests • Medications • Consultation requests

	• Nursing orders	• Nursing orders
Decision Support (DS)	• Clinical guidelines • Clinical reminders • Drug allergy alerts • Drug-drug interaction alerts • Drug-lag interaction alerts • Drug dosing support	• Drug allergy alerts • Drug-drug interaction alerts • Drug-lag interaction alerts • Drug dosing support

* Adopted from American Hospital Association (AHA)

Prior EHR literature has investigated the direct effect of specific features of EHR (e.g. Garg et al. 2005; Eslami et al. 2008; Bayoumi et al. 2014) but rarely showed the indirect effects of a collective set of EHR features which concurrently influence clinical outcome. Under the current healthcare law, the use of EHR feature can be equated with "the meaningful use of HIT" (Jha et al. 2009; Jha et al. 2010; Blavin et al. 2010;Jha et al. 2011; DesRoches et al. 2012) and there are also a few studies measuring the importance of meaningful use of HIT (e.g. Hah and Bharadwaj 2012). In fact, the meaningful use of HIT is conceptualized as the use of certified EHR system features to improve clinical outcome, engage in patient in the care process, enhance care coordination, and maintain privacy and security of patient health information (HealthIT.gov) and indeed, it is similar in that both acknowledge the important role of EHR features on clinical outcome. However, meaningful use of HIT measures are not only broad concept that encompass care provider, patients, and third-party organizations but also the measures are geared toward rewarding eligible hospitals and office-based physicians for their adherence to HIT adoption and utilization rules. Our focus is more limited to the EHR feature use in a care service dyad within the hospital and considers rather localized performance improvement. Since when IT impacts truly exist, it can be identified at lower operational levels in a firm (e.g. strategic business unit), at or near the site where the domain-specific technology is implemented (p 6, Barua et al. 1995). In other words, a technology and its features influence the related business processes and activities in a close proximity, and such accumulated impacts are revealed at most related local performance. A local performance or an intermediate level of firm performance then function as *a priori* to a higher level outcome. Therefore, we claim that investigation on the impacts of EHR features on local performance can provide more detailed view of the value creation by the EHR features and differences in localized clinical outcome.

3.2.4. Dimensions of Hospital–level Clinical Outcome

An important "localized" clinical outcome is a patient's length of stay (LOS). LOS refers to the number of bed days per inpatient episode and serves as a proxy for hospital efficiency (Berki et al. 1984; Siciliani et al. 2013). In our research context, we examine LOS as a hospital level clinical outcome that is likely to be impacted by the information processing capability from admission to discharge. On admission, admission decision depends on information such as pre-operative screening, medication and planning for diagnostic tests. During stay, information on bed availability is critical for patient transfers in between outpatient wards and inpatient wards. At discharge, information of expected day of discharge should be released to patients and their family without delays (Borghans et al. 2012). Thus, LOS is contingent on information acquisition, analysis, and interpretation throughout an entire patient care plan (Berki et al. 1984) and therefore a capability of processing information coming from patients, physicians, and the care setting can affect LOS (Martin and Smith 1996). Amongst some factors that affect the overall level of LOS, it is noted that at an organizational level, hospital focus (Hyer et al. 2009; KC and Terwiesch 2011; Clark and Huckman 2012), hospital profit status (Burns and Wholey 1991), and prospective payment (Norton et al. 2002) have been associated with LOS. At a workgroup level, physician workload (KC and Terwiesch 2009) and patient flows (KC and Terwiesch 2012), care coordination (Gittell et al. 2000; Gittell et al. 2002), patient severity (Knaus et al. 1993), and care complexity (Berki 1984; Goldfarb et al. 1983) have been examined in explaining the variation in LOS. Lastly, at the individual level, the workload of physicians (Lawton and Wholey 1991; Chen and Naylor 1994; Szlzarulo et al. 2011) has also been shown to affect LOS. It is worth noting that as the unit of analysis in determinants of LOS becomes more granular from the organizational level to individual level, the factors that influence LOS are closely related to the level of information processing capability in a variety of care tasks and/or task environment.

3.2.5. Linking the Feature Use of EHR to Hospital Outcome

In this chapter, I propose that the fit between clinical tasks and feature use of EHR can enhance clinical outcome. While there have been various definitions of fit (Venkatraman 1989), we define fit between care tasks and EHR features as moderation such that the interaction effects of clinical tasks (or task environments) and EHR features have positive implications for clinical outcome. With increased information processing capability, hospitals can reduce the ambiguity and uncertainty of the tasks (Galbraith 1977; Daft and Lengel 1984, 1986) or increase coordination (Keller 1994). In this paper, we anticipate that EHR-enabled information processing capability can augment the positive impacts or mitigate negative impacts of care tasks/task environment on LOS.

EHR-feature driven information processing capability can occur at three levels of a hospital. First, at an organizational level, EHR functionalities such as electronic clinical documentation (ECD), result viewing (RV), and bar coding (BC) can enable clinicians to create the unified clinical reports that maintain data such as patient demographics, test results from laboratory and radiology, and medication lists and such electronic information can be easily shared across different hospital units. Next, at a workgroup level, the use of EHR features can better streamline information sharing processes among different departments via a unified system interface. In fact, result viewing (RV) is linked to laboratory and radiology department whereas bar coding (BC) interfaces with pharmaceutical administration and computerized practitioner order entry (CPOE) links related care providers per a clinical order. Such EHR features can automate department-to-department interactions so that diagnostic and therapeutic processes are seamlessly operated. Although paper-based charts have also delivered the aggregated information between clinical departments in the hospital, paper-based health information is sequentially recorded such that those charts are not accessible by multiple clinicians all at once. Thus, EHR's ubiquitous and real-time attributes can change the way how health information is created, shared, and communicated at a workgroup level. Lastly, at an individual level, the use of EHR features can enhance physician's clinical decision making processes by structuring clinicians' tacit knowledge. In general, care plans for each patient depend on the sole discretion of the attending physicians. Physicians' tacit knowledge, experience and hunches are often stored in their minds (Alavi and Leidner 2001) such that it is a challenge to transform physicians' unstructured knowledge into the structured and sharable knowledge for resolving ambiguous clinical problems. As such, decision support (DS) systems can provide individual physicians with structured rules for cross-checking his or her knowledge with external information reference such as drug-drug interactions and/or external clinical guidelines. Together with personal knowledge management, accessibility to the internally-accumulated health information from multiple sources may create an environment in which physicians make appropriate clinical decisions with quality information in a timely manner.

3.2.6. Hypotheses

The discussion above has argued that care task contingencies are influenced by the differential use of EHR features whose information processing capabilities can then lead to improved patient length of stay (LOS). More specifically, we propose that the impacts of hospital focus, patient severity, care complexity and physician workload on LOS can be influenced by differential feature use of EHR.

3.2.6.1. Hospital Focus

Focused hospitals can reduce LOS from both patient selection and superior service delivery (KC and Terwiesch 2011) as focused hospitals' well-developed specialty care plans can reduce complexity and uncertainty of care tasks (KC and Terwiesch 2011; Hyer et al. 2009; Clark and Huckman 2012). Although hospital-level focus has been shown to enhance LOS, hospitals can reap even greater benefits from the use of EHR by automating information collection and sharing processes which provides a basis for better patient selection and further patient data analysis. For better patient selection, access to electronic patient demographics and medication history, ahead of patient selection, allows focused hospitals' routine selection processes to be more accurate and swift. Moreover, for the superior service delivery, EHRs can also complement to the related health information technologies (HIT) in the focused hospitals so that they can improve their overall clinical productivity and patient safety. For example, Huntington Memorial Hospital, a 625-bed, not-for-profit hospital in Pasadena (CA), has adopted electronic health records (EHR) and complementary EHR technologies as they aim at creating a predictive model for adverse patient outcomes e.g. hospital-introduced infections in advance (Cerner 2012). Thus, EHR can not only affect focused hospitals' processes of patient selection with electronically-collected information but also provide superior service environments through a capability of advanced patient data analysis.

H1: The use of EHR systems augments the positive effect of focus on clinical outcome

3.2.6.2. Patient Severity

Patient severity is the risk of death, or complications due to comorbid diseases (Charlson et al. 1987). When patients' symptoms are severe at time of admission (Knaus et al. 1993) or the quantity of treatment provided to the patient is increased (Godfard et al. 1983), patients generally have longer LOS. When patient's *ex ante* diseases are in a range of severe comorbid conditions, there is a greater uncertainty associated with the likelihood of patient mortality in the coming years. In this case, the use of EHR feature can increase workgroup's information processing capabilities in that information on patients' comorbid diseases, the number of diagnostic tests and the relevant treatments are ordered, collected, and shared electronically across units. Electronic health records can therefore facilitate diagnosis, testing and therapy (e.g. RV), and enhance communication amongst a range of providers involved in the care of a given patient.

H2: The use of EHR systems mitigates the negative effect of patient severity on clinical outcome

3.2.6.3. Care Complexity

Care complexity is associated with the degree of difficulty in treating a given patient. Patient complexity gives rise to greater uncertainty, as there might be unforeseen complications or interactions from medication and clinical procedures. It may also increase ambiguity as care teams are required to prioritize care plans depending on the set of diagnoses. Prior literature suggests that the number of diagnostic tests is associated with the level of LOS (Berki et al. 1984). The uncertainty resulting from *care complexity*, however, can be reduced when care teams efficiently use EHR systems for their diagnosis decisions. As the volume of health information increases, the ability to aggregate the whole information together for the final diagnosis may play a significant role in reducing LOS. Through the EHR systems, clinicians can access patient specific data to determine the efficacy of various therapies (Knaus et al. 1993). Moreover, EHR enables care providers to reduce unnecessary inter-unit communication and to streamline information sharing processes via structured interfaces with ancillary service departments (e.g. RV and/or BC). The appropriate treatment followed by precise diagnosis will therefore positively enhance clinical outcome. Therefore,

H3: The use of EHR systems mitigates the negative effect of care complexity on clinical outcome

3.2.6.4. Physician Workload

Patient volume has been shown to increase the LOS of the physician's patients (Burns and Wholey 1991). When a physician has more patients under her care, she may allocate smaller amounts of service time per patient, or alternatively increase dependence on available slack resources (e.g. asking assistance from colleagues). In that situation, EHR allows physicians to access the anticipated examination time using detailed patient information e.g. ECD and thereby manage patient treatment schedules more effectively (Salzarulo et al. 2011). In other words, electronic health information is consumed and interpreted as a source for categorizing patients into different groups so that physicians can efficiently allocate their time and execute further care plans. Moreover, physicians may also minimize wasted time with automated communication across the care teams via CPOE. In fact, a physician's clinical orders can be made by CPOE system operation such that unnecessary interactions for routine tasks (e.g. phone calls) can greatly be reduced. Instead, expanded traceability per a care episode can enable a physician and other clinicians to collaborate with one another electronically. Thus, the use of EHR can enhance a physician's ability to manage workload and coordinate care across multiple care providers simultaneously.

H4: The use of EHR systems mitigates the negative effect of physician workload on clinical outcome

3.3. Methods

Our empirical analysis is based on secondary sources of dataset published by the Office of Statewide Health Planning and Development (OSHPD), which includes observations for California cardiac patients' length of stay and patient volume, number of diagnosis on admission, and the number of cardiology physicians per a hospital during 2008-2010. The OSHPD datasets consists of a record for each inpatient discharged from a California licensed hospital including general acute care, acute psychiatric, chemical dependency recovery, and psychiatric health facilities. For privacy protection, some of patient's detailed information e.g. ID and zip code are masked. In addition, measures of EHR use are obtained from the American Hospital Association (AHA) EHR adoption data during 2008-2010. The AHA EHR database details the level of hospitals' adoption status in multiple system categories in ECD, RV, CPOE, DS, and BC on a continuum of "implemented across all units" to "not in place and not considering implementation." In addition, we also added a comprehensive set of patient as well as hospital level covariates in our research model. Total sample size (i.e. total number of cardiac patients in California) is 1,091,474 and the number of hospital is 403.

Our dependent variable, patient level length of stay (LOS) is measured as the total number of days from admission to discharge date. Although our dependent variable is an intermediate measure that can lead to the ultimate outcomes e.g. financial performance and quality of care, it is reasonable to consider the impacts of EHR use on a clinically-related outcome measure in the more granular clinical settings. Next, based on these triangulated dataset, we computed our four independent variables - *focus, patient severity, care complexity, and physician workload*. First, *focus* is defined by a hospital's care concentration and measured by the percentage of patients admitted for cardiology reasons (KC and Terwiesch 2011). *Patient severity* is defined as the risk of death from comorbid diseases and measured by Charlson index or a weighted index based on the number and the seriousness of comorbid disease (Charlson et al. 1987). *Care complexity* refers to the level of difficulty in treating a patient as measured by the total number of diagnoses per a patient. Finally*, physician workload* is defined as the average volume of work assigned to cardiology physicians and computed as the total number of cardiac patients divided by total number of cardiology physicians. Third, for a moderator variable, sub-dimensional EHR use is computed as a summated scale of the items in ECD, RV, CPOE, DS, and BC respectively. Table 10 depicts each item for the EHR functionalities. When an item in subcategory of EHR is implemented across all hospital units, it is counted as one. Then, the items were subject to a factor analysis in order to derive reflective measures of sub-dimensional EHR use. The summated scale of EHR use in each sub-dimension (e.g. ECD and RV) is computed as the total number of EHR functionality implemented across all units divided by total number of EHR functionality listed. For item *i* in a sub-dimensional EHR (e.g. ECD, RV, CPOE, DS, and BC), EHR use is summed up to total number of SubEHR *k*. Thus, subdimensional EHR use is computed in equation (1)

$$EHRUse_i = \frac{1}{N(K,i)} \sum_i SubEHR_i$$

We next compute a formative measure across all five EHR categories in ECD, RV, CPOE, DS and BC as shown in Table 11. As baseline in each equation, we look at both average impacts of EHR use and differential impacts of five sub-dimensional measures of EHR use on the link between hospital contingent factors and LOS.

Table 11. Descriptive Statistics and Correlation Matrix for the EHR Use Variable

		Mean	SD	1	2	3	4	5
1	EHR Use	0.35	0.28					
2	USE_ECD_R	0.27	0.42	0.75				
3	USE_RV_R	0.72	0.44	0.76	0.40			
4	USE_CPOE_R	0.18	0.35	0.69	0.51	0.32		
5	USE_DS_R	0.33	0.41	0.77	0.43	0.49	0.46	
6	USE_BC_R	0.25	0.32	0.65	0.36	0.46	0.27	0.37

Our study also includes a number of key covariates. To account for patient-specific effects that could influence outcome, we control for patient demographic factors i.e. patient age, gender, and race, patients' insurance and payment i.e. insurance conditions i.e. Medicare and total charge of medical care, and patients' hospital selection effect i.e. admission type (e.g. scheduled/unscheduled/infant), and travel distance between a patient's domicile and a focal hospital. We also control for a range of clinical conditions that have been known to affect outcome including myocardial infarction for current admission, prior myocardial infarction, peripheral vascular disease, diabetes, and hypertension. Additionally, we include hospital-level control variables that affect outcome such as hospital age, hospital size as measured by the number of staffed beds, teaching status, and health service area in order to control for hospital market effect. In addition, we control for type of coverage such as managed care vs. traditional coverage since insurers or third-party payers can affect hospitals' behaviors of patient admission and discharge (Santerre and Neun 2010).

As preliminary tests, the normality of the dependent variable and multicollinearity among all independent variables were checked. Correspondently, LOS is log-transformed in order to reduce the skewness in distribution. We do not find any significant multicollinearity amongst the independent variables. In particular, the variance inflation factor (VIF) is less than a threshold of 10.

3.4. Model Specification: Hierarchical Linear Modeling (HLM)

Then, we regressed length of stay (LOS) on four contingent factors and other covariates using Hierarchical Linear Modeling (HLM). HLM is useful when variables of interest are measured at different levels and researchers want to see how variables at one level affect relationship between other variables measured at another level (Raudenbush et al. 2002). Conceptually, in our dataset, an individual patient's length of stay (dependent variable) is actually nested within care departments and within hospitals. Thus HLM in our context is employed to capture multilevel variations that possibly affect hospitals' care decision and use of IT across the department and within a hospital. We compare the results from two-level HLM model and three-level HLM model such that (1) two-level hypothesis is to consider the separate fit between four factors and EHR features and (2) three-level HLM models include all variables and explore the combined fit between four factors and EHR features.

Two-level HLM Model

Level 1: Across patients within a hospital (for ith patient and kth hospital)

Log (LOS) = $\beta_0 + \beta_1 Care\ Contingency + \sum_m \beta_m\ PatientCharacteristics + \varepsilon$

Level 2: Across hospitals

$$\beta_0 = \gamma_{00} + \gamma_{01}ECD + \gamma_{02}RV + \gamma_{03}CPOE + \gamma_{04}DS + \gamma_{05}BC + \sum_l \gamma_{0l}\, Hospital\ Controls + \mu_0$$

$$\beta_1 = \gamma_{10} + \gamma_{11}ECD + \gamma_{12}RV + \gamma_{13}CPOE + \gamma_{14}DS + \gamma_{15}BC + \mu_1$$

Three-level HLM Model

Level 1: Across patients within a group (for i^{th} patient, j^{th}group and k^{th} hospital)

$$Log\ (LOS)_{ijk} = \beta_{0jk} + \beta_{1jk}Severity + \beta_{2jk}Complexity + \sum_m \beta_{mjk}\ PatientCharacteristics + \varepsilon_{ijk}$$

Level 2: Across group within a hospital

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01k}ECD + \gamma_{02k}RV + \gamma_{03k}CPOE + \gamma_{04k}DS + \gamma_{05k}BC + \mu_{0jk}$$

$$\beta_{1jk} = \gamma_{10k} + \gamma_{11k}ECD + \gamma_{12k}RV + \gamma_{13k}CPOE + \gamma_{14k}DS + \gamma_{15k}BC + \mu_{1jk}$$

$$\beta_{2jk} = \gamma_{20k} + \gamma_{21k}ECD + \gamma_{22k}RV + \gamma_{23k}CPOE + \gamma_{24k}DS + \gamma_{25k}BC + \mu_{2kjk}$$

Level 3: Across hospitals

$$\gamma_{00k} = \delta_{000} + \delta_{001}Focus + \delta_{002}Workload + \sum_n \delta_{00n}\ Hospital\ Controls + \epsilon_{000}$$

$$\gamma_{10k} = \delta_{100} + \delta_{101}Focus + \delta_{102}Workload + \epsilon_{100}$$

$$\gamma_{20k} = \delta_{200} + \delta_{201}Focus + \delta_{202}Workload + \epsilon_{200}$$

3.5. Results

Table 12 describes descriptive statistics and pair-wise correlation between variables. We see that the average length of stay for California cardiac patients is 4.57 days. In the correlations, we notice that bivariate correlations between health service area, hospital age, and hospital size are high (0.707, 0.818, and 0.735). Since our sample size is relatively large (n=1,091,474), it is unlikely that multicollinearity among covariates biases our results. In each table, the moderator, EHR use has five sub-dimensionalities of electronic clinical documentation (ECD), result viewing (RV), computerized physician order entry (CPOE), decision support (DS), and bar coding (BC) and its unidimensional composite measures as the baseline in the model.

Table13 presents that main effects of focus, patient severity, and care complexity were all significant and in the expected direction except physician workload. More specifically, while focus was expected to be negatively associated with LOS, patient severity and care complexity are expected to be positively related to LOS. Physician workload was negatively significant in the model. For the interaction effects, first, the coefficient of ECD*focus (FOC) and BC*FOC are negative and significant at $p<0.0001$. Thus hypothesis 1 is partially supported. Second, the impact of RV*patient severity (SEV) ($p<0.0001$) is negatively associated with LOS. Third, RV*care complexity (COM) ($p<0.0001$) and BC*care complexity (COM) are negatively related to LOS. Hence hypothesis 2 and 3 are supported. Finally, the estimated coefficient of CPOE* physician workload (WORK) and BC* physician workload (WORK) are negatively associated with LOS which support our hypothesis 4 at $p<0.0001$. We noticed that some estimated coefficient of sub-dimensional EHR use measure such as DS was reversely correlated with LOS i.e. positive and significant. This result may be explained by the fact that DS systems that are embedded into well developed, and comprehensive CPOE systems are regarded as the only method to significantly impact clinical decision-making (Staggers et al. 2008). For this reason, our results may indicate that stand-alone EHR use in DS may reversely increase the number of alternatives for patient care options.

Table 12. Descriptive Statistics and Correlation Matrix

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1 **LOS (Days)**	4.57	23.31																												
2 **EHR Use_ECD****	0.27	0.42	-0.016																											
3 **EHR Use_RV**	0.72	0.44	-0.010	0.402																										
4 **EHR Use_CPOE**	0.18	0.35	-0.017	0.506	0.321																									
5 **EHR Use_DS**	0.33	0.41	-0.028	0.428	0.487	0.455																								
6 **EHR Use_BC**	0.25	0.32	-0.020	0.355	0.462	0.268	0.369																							
7 **Focus**	0.15	0.07	-0.035	-0.060	-0.040	-0.024	-0.054	0.022																						
8 **Patient Severity**	10.63	5.04	0.216	0.003	-0.033	0.023	0.008	-0.009	-0.002																					
9 **Care Complexity**	1.20	1.38	0.481	0.036	-0.008	0.076	0.039	0.008	-0.052	0.492																				
10 **Physician Workload**	34.06	187.30	-0.006	0.053	-0.005	-0.054	-0.071	0.110	0.001*	0.002*	-0.002																			
11 **Total Charge ($)**	58423.44	112130.58	0.603	-0.091	0.074	-0.206	-0.118	0.046	0.048	0.049	0.165	0.034																		
12 **Medicare**	0.55	0.50	0.121	0.013	-0.013	0.020	0.018	0.030	0.047	0.179	0.272	0.005	0.051																	
13 **Hispanic**	0.13	0.33	0.025	-0.049	0.002*	-0.032	-0.005	-0.042	-0.072	0.060	-0.022	0.026	0.028	-0.067																
14 **Male**	0.42	0.49	-0.015	0.010	0.024	-0.001*	0.012	0.016	0.001*	0.049	0.016	0.004	0.009	-0.041	0.045															
15 **MYOCARDIAL INFARCTION**	0.07	0.26	0.079	0.013	-0.009	0.014	0.006	0.015	0.040	0.023	0.064	-0.026	0.058	0.008	-0.018	0.025														
16 **OLD MYOCARDIAL INFARCTION**	0.11	0.32	-0.014	0.039	0.009	0.021	0.023	0.011	0.011	0.294	0.161	0.001*	-0.038	0.042	-0.016	0.058	-0.007													
17 **CHF**	0.27	0.44	0.223	0.002*	-0.023	0.005	0.004	-0.012	-0.009	0.274	0.331	-0.013	0.096	0.152	0.008	0.006	0.050	0.084												
18 **PERIPHERAL VASCULAR DISEASE**	0.06	0.24	0.086	0.002*	-0.009	0.009	-0.001*	0.010	0.017	0.281	0.155	-0.003	0.041	0.089	-0.003	0.033	0.010	0.040	0.041											
19 **PERIPHERAL (DX) VASCULAR DISEASE**	0.01	0.11	0.095	-0.005	-0.009	-0.005	-0.014	0.001*	0.008	0.080	0.029	-0.006	0.069	0.026	-0.014	0.009	-0.017	0.004	-0.033	0.092										
20 **CEREBROVASCULAR(S) DISEASE**	0.03	0.16	0.079	0.013	0.002*	0.015	0.007	0.007	0.006	0.051	0.118	-0.003	0.049	0.063	-0.014	-0.006	0.024	0.015	0.010	0.052	0.014									
21 **COPD**	0.19	0.39	0.112	-0.016	-0.019	-0.002	-0.015	0.010	0.011	0.340	0.220	0.002*	0.058	0.092	-0.050	-0.005	0.004	0.027	0.160	0.054	0.020	0.021								
22 **DIABETES**	0.26	0.44	0.040	-0.023	-0.003	-0.044	-0.007	-0.012	0.019	0.320	0.112	0.006	0.074	0.028	0.087	0.006	0.019	0.056	0.077	0.027	0.004	0.018	0.017							
23 **DIABETES W/ SEQUELAE**	0.08	0.27	0.108	0.018	-0.022	0.048	0.025	-0.020	-0.023	0.572	0.288	-0.001*	-0.053	0.062	0.063	0.014	0.010	0.033	0.117	0.067	0.005	0.012	0.004	-0.097						
24 **HYPERTENSION**	0.32	0.47	0.013	-0.013	-0.028	-0.006	-0.014	0.003	0.073	0.124	0.047	-0.072	-0.001*	0.068	0.000*	-0.010	0.163	0.031	0.114	0.056	0.048	0.017	0.025	0.091	0.048					
25 **Distance (Miles)**	48.06	351.75	-0.005	0.002	-0.002*	0.003	-0.005	0.008	0.010	-0.029	-0.021	0.000*	0.013	-0.025	-0.044	-0.090	0.003	-0.001*	-0.018	-0.005	0.000*	-0.001*	-0.012	-0.014	-0.015	-0.011				
26 **Health Service Area**	2.66	4.64	-0.005	0.087	0.267	0.040	0.089	0.122	-0.014	0.005	-0.051	0.035	0.031	-0.008	0.022	0.006	0.070	0.004	0.033	0.010	0.016	-0.002	-0.007	0.016	-0.003	0.264	-0.007			
27 **Teaching Status**	0.00	0.07	-0.008	-0.007	0.044	-0.036	-0.056	-0.012	-0.007	-0.007	-0.034	-0.041	-0.004	-0.057	0.044	0.000*	0.007	0.000*	0.002*	0.000*	0.001*	-0.006	-0.015	0.011	-0.006	0.058	-0.001*	0.125		
28 **Hospital Age**	12.46	27.17	-0.001*	0.089	0.232	0.007	0.108	0.028	-0.078	0.002	-0.046	-0.035	0.000*	-0.027	0.014	0.012	0.057	0.004	0.028	0.007	0.011	-0.002*	-0.006	0.009	0.000*	0.222	-0.009	0.707	0.092	
29 **Hospital Size (# Doctors)**	66.41	193.11	-0.007	0.166	0.286	0.071	0.112	0.151	-0.032	0.015	-0.030	-0.033	-0.002*	-0.022	-0.005	0.012	0.074	0.011	0.035	0.017	0.023	0.000*	-0.004	0.009	0.005	0.256	-0.008	0.818	0.148	0.735

Table 13. Two-level HLM Results of the Fit between EHR Features and Care Contingencies (Five Different Models)

	DV: Log (A Patient's Length of Stay)				
Care Contingency	(1) Baseline for Comparison	(2) Focus	(3) Patient Severity	(4) Care Complexity	(5) Physician Workload
Intercept	1.1276**	-1.1788*	-1.082**	-0.9379**	-1.1709**
	(19.57)	(0.07643)	(0.07955)	(0.06237)	(0.07404)
Focus		-0.7453***			
		(0.1308)			
Patient Severity			0.0478***		
			(0.0012)		
Care Complexity				0.0345***	
				(0.0001)	
Physician Workload					-0.00004**
					(0.00001)
EHR feature_ECD		-0.2034***	-0.1758***	-0.1427***	-0.18140***
		(0.0013)	(0.0046)	(0.0101)	(0.00429)
EHR feature_RV		0.0277**	0.0105***	-0.0494***	-0.01903***
		(0.0073)	(0.0026)	(0.0038)	(0.00351)
EHR feature_CPOE		0.2712***	0.2805***	0.2266***	0.27880***
		(0.0077)	(0.0176)	(0.0248)	(0.01913)
EHR feature_DS		-0.0384***	-0.0446**	-0.0862***	-0.02543**
		(0.0002)	(0.0128)	(0.0138)	(0.01263)
EHR feature_BC		-0.0811***	-0.0409***	-0.0267***	-0.00131
		(0.0086)	(0.0024)	(0.0031)	(0.00271)
ECD*Care Contingency		-1.4926***	0.0104***	0.0074***	0.00002
		(0.0783)	(0.0016)	(0.0012)	(0.00003)
RV* Care Contingency		0.1627	-0.0122***	-0.0092***	0.00010***

	(0.1588)	(0.0026)	(0.0010)	(0.000002)
CPOE* Care Contingency	0.0247	0.0112***	0.0083***	-0.00019***
	(0.2555)	(0.0013)	(0.0012)	(0.00004)
DS* Care Contingency	1.7963**	0.0117***	0.0094***	0.00001
	(0.5332)	(0.0007)	(0.00004)	(0.00003)
BC* Care Contingency	-1.0528***	-0.0004	-0.0061**	-0.00009***
	(0.1997)	(0.0047)	(0.0029)	(0.00002)

*** p<.0001; **p<.001; * p<0.1. Patient level controls (i.e. age, gender, race, total charge, payment type (Medicare), admission type (scheduled/unscheduled/infant), travel distance, clinical conditions: myocardial Infarction, prior myocardial Infarction, peripheral vascular disease, diabetes, hypertension and payer type) and hospital level controls (i.e. hospital age, size, teaching status, and health service area) are included in the research model but omitted in the result table.

Table 14 further analyzes the combined fit between EHR features and four care contingencies in one single model. It shows that at the concurrent presence of multiple interactions and other contingency factors, the results of focus and care complexity obtained from two-level HLM models are similar with those from three-level HLM models but size of the regression coefficients are changed. In fact, while significance of ECD*focus and BC*focus is remained at $p<0.0001$, negative coefficient of ECD*focus became larger and that of BC*focus became smaller. Additionally, coefficients of CPOE* care complexity and BC*care complexity were larger than two-level HLM models. On the other hand, significance of patient severity and physician workload are changed such that (1) CPOE*patient severity and DS*patient severity were negatively associated with LOS reduction and (2) ECD*physician workload became salient in the combined model. These results from three-level HLM model indicates that care contingency variables that are related to individual characteristics – patient severity and physician workload may be vulnerable to the presence of other confounding factors in the care service dyads.

Table 14. Three-level HLM Results of the Fit between EHR Features and Care Contingencies (Single Model)

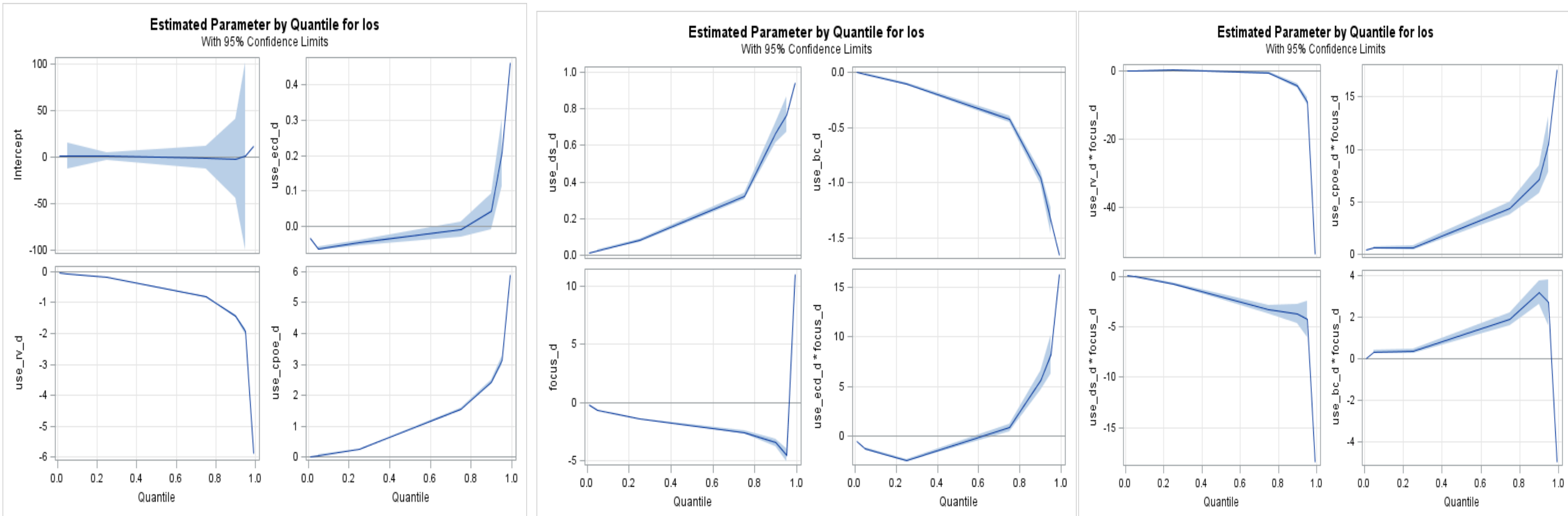
DV: Log (A Patient's Length of Stay)					
		Focus	Patient Severity	Care Complexity	Physician Workload
Care Contingency		-0.1232 (0.1128)	0.0131*** (0.0012)	0.0339*** (0.00002)	0.00001 (0.00002)
EHR feature_ECD	-0.1421*** (0.0216)				
EHR feature_RV	-0.0014 (0.0081)				
EHR feature_CPOE	0.2467*** (0.0043)				
EHR feature_DS	-0.1681*** (0.0193)				
EHR feature_BC	-0.0993*** (0.0031)				
ECD* Contingency		-2.3272*** (0.0787)	-0.0043*** (0.0009)	0.0077*** (0.0009)	-0.0002*** (0.00004)
RV* Contingency		-0.2871 (0.3251)	0.0060*** (0.0003)	-0.0106*** (0.0005)	0.0001*** (0.000004)
CPOE* Contingency		0.8251* (0.3205)	-0.0114*** (0.0016)	0.0109*** (0.0002)	-0.0001 (0.0001)
DS* Contingency		2.1279** (0.6029)	-0.0063*** (0.0012)	0.0109*** (0.0006)	0.0001 (0.0001)
BC* Contingency		-0.5467*** (0.0298)	0.0077** (0.0021)	-0.0063** (0.0032)	0.0001*** (0.00003)

*** p<.0001; **p<.001; * p<0.1. Patient level controls (i.e. age, gender, race, total charge, payment type (Medicare), admission type (scheduled/unscheduled/infant), travel distance, clinical conditions: myocardial Infarction, prior myocardial Infarction, peripheral vascular disease, diabetes, hypertension and payer type) and hospital level controls (i.e. hospital age, size, teaching status, and health service area) are included in the research model but omitted in the result table. In addition, higher term interactions of Patient Severity*EHR features* Focus, Care Complexity* EHR features * Focus, and Workload* EHR features * Focus are excluded from the result table.

3.6. Post-hoc Analysis

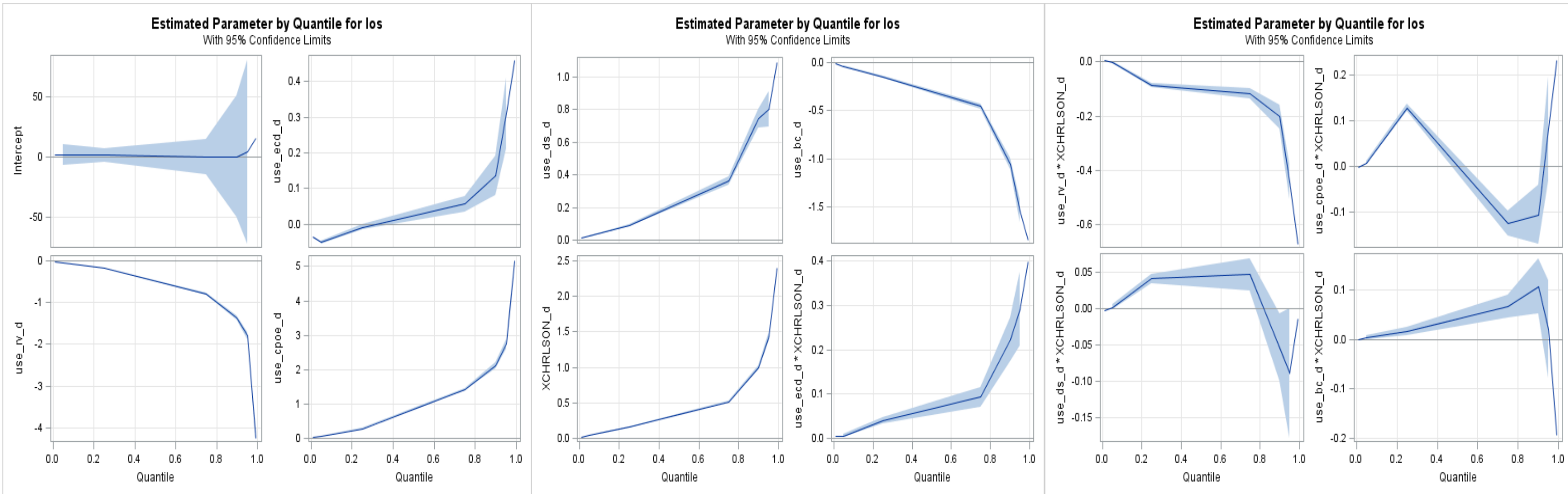
In order to account for the possibility that patient heterogeneity may influence the adoption of different EHR functionalities, we ran cross-section quantile regression to further investigate the degree to which the results obtained from HLM are modified by patient heterogeneity. In traditional OLS assumptions, distribution of error term is to be normal such that the impacts of focal variables are equally distributed and thus, outliers should be carefully examined and treated. However, in a healthcare context, patients are in fact heterogeneous – they are different from their health conditions to symptoms but they are examined or treated by the same clinical technologies in the focal hospital. In this light, we assume that the effects of EHR use may not be the same for all patients accordingly. Then, patients' extreme cases of length of stay are no longer a subject of outliers but important to measure how a hospital manages such cases with the improvement of EHR systems. Quantile regression can reflect our assumptions in that it bases on conditional distribution of DV, while making no distributional assumption about the error term in the model (Koenker and Bassett 1978). Our quantile plots indicate that although overall results are same with the OLS regression results, the use of EHR disproportionately amplifies or mitigates the impacts of four hospital contingencies on shorter vs. longer LOS. As patients' hospital stay increases, the augmented effect of focus and mitigated effect of patient severity, care complexity, and physician workload are differentiated by the use of EHR systems as shown in Figure 5 through 7. Here, X axis represents the quantile of patients' length of stay such that lower quantile means short LOS whereas Y axis represents the regression coefficients of the main effects and interaction effects between four independent variables and EHR with 95% confidence limits in the shaded area. For H1, use of ECD when hospital maintain clinical specialty (focus) reduce LOS for lower quantile patients who has shorter LOS than upper quantile patients in Figure 5. For H2, the use of RV on the relationship between patient severity and LOS demonstrates that RV was effective for very short LOS patients and for extremely long LOS patients. For H3, the use of RV on the link of care complexity- LOS shows that the use of RV mitigates the negative impacts of care complexity on all ranges of LOS patients. For H4, the use of CPOE was salient for lower and upper quantile LOS patients. Thus, the results from both HLM and quantile regression indicate that ECD, RV and CPOE are salient to an individual patient's length of stay within the focal hospital.

Figure 5. Quantile Process Plots on the Moderation Effects of EHR Feature Use on Focus (FOC)-LOS Link



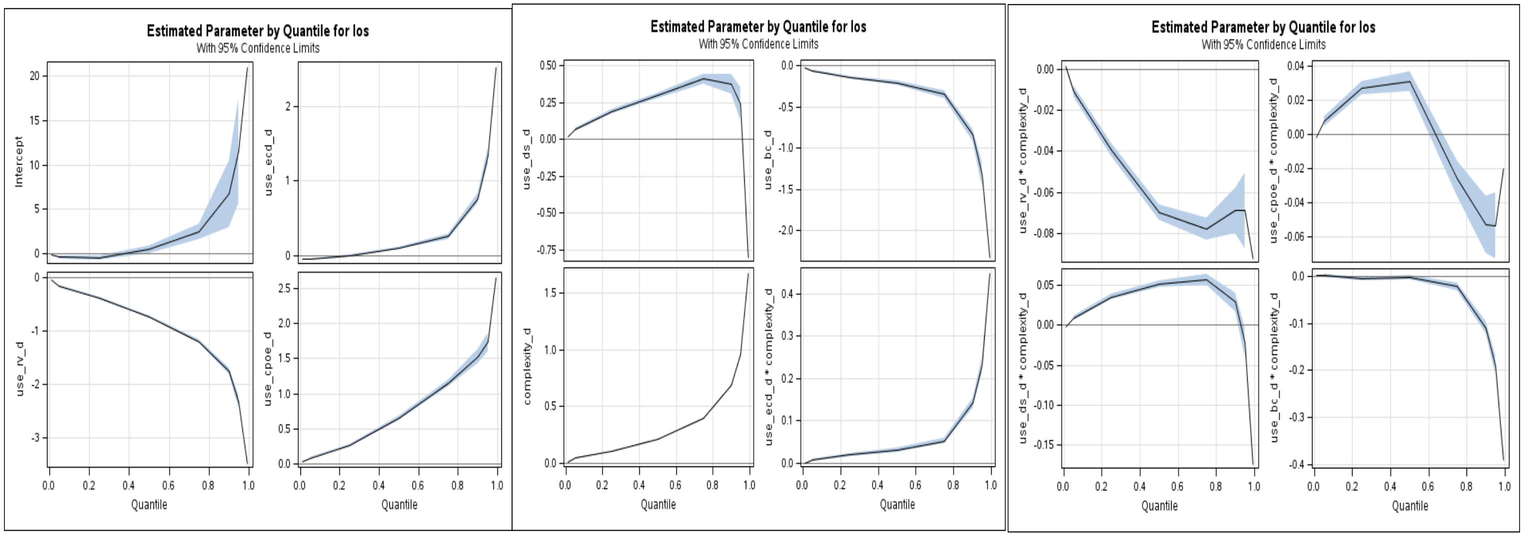
Notes. X axis represents the quantile of patients' length of stay such that lower quantile means short LOS whereas Y axis represents the regression coefficients of main effects and interaction effects between four independent variables and EHR, with 95% confidence limits (e.g. shaded area).

Figure 6. Quantile Process Plots of Moderation Effects of EHR Feature Use on Patient Severity (SEV)-LOS Link



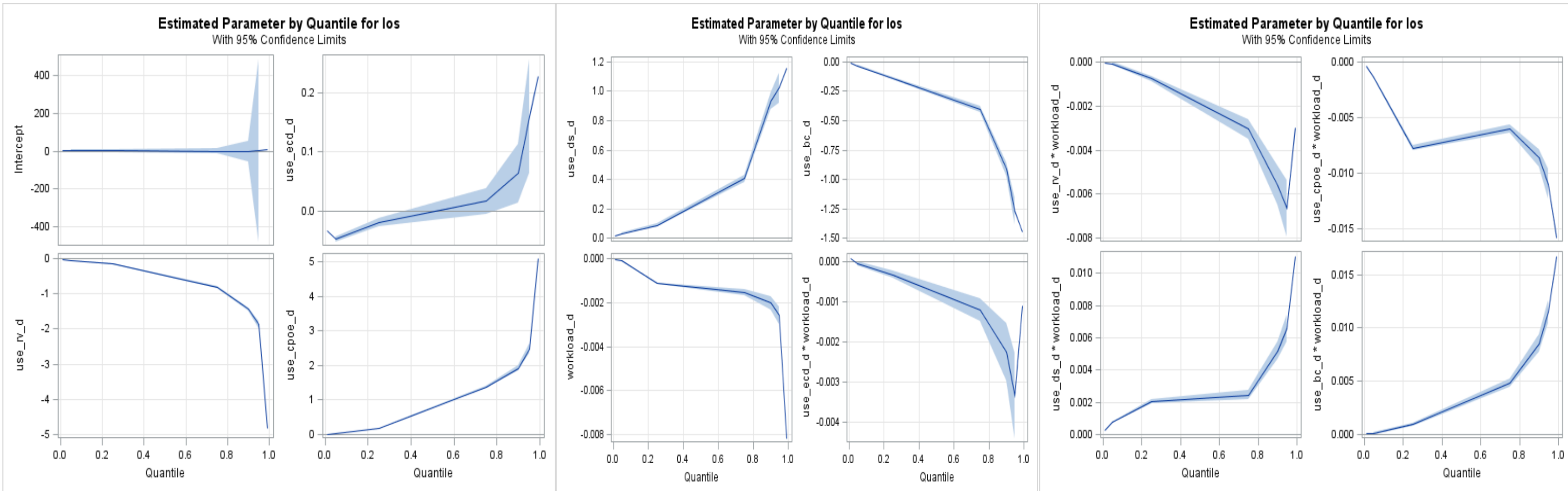
Notes. X axis represents the quantile of patients' length of stay such that lower quantile means short LOS whereas Y axis represents the regression coefficients of main effects and interaction effects between four independent variables and EHR, with 95% confidence limits (e.g. shaded area).

Figure 7. Quantile Process Plots of Moderation Effects of HER Feature Use on Care Complexity (COM)-LOS Link



Notes. X axis represents the quantile of patients' length of stay such that lower quantile means short LOS whereas Y axis represents the regression coefficients of main effects and interaction effects between four independent variables and EHR, with 95% confidence limits (e.g. shaded area).

Figure 8. Quantile Process Plots of Moderation Effects of EHR Feature Use on Physician Workload (WORK)-LOS Link



Notes. X axis represents the quantile of patients' length of stay such that lower quantile means short LOS whereas Y axis represents the regression coefficients of main effects and interaction effects between four independent variables and EHR, with 95% confidence limits (e.g. shaded area).

3.7. Discussion and Conclusion

This study examined that impact EHR feature use on clinical outcome in a healthcare service setting. Grounded in the feature centric view of IT and IT use literature, we propose that feature use of EHR can differentially influence four contingent care tasks– hospital focus, patient severity, care complexity, and physician workload and confer better clinical outcome. Our findings based on large sample of patient discharge data over 2008-2010 suggested that the fit between EHR feature use and organizational tasks help hospitals significantly decrease patient length of stay (LOS). Even among the heterogeneous patients who have various level of LOS, EHR feature use was disproportionately effective for the shorter versus longer LOS patients. While prior literature examined the effects of EHR in various contexts, this is one of the first studies to provide empirical evidence that EHR benefits vary across different functionalities and across different categories of patients.

The results from this study suggest that EHR differentially help hospitals cope with various care situations by allowing care providers to create, access, and retrieve real-time electronic health information, and to automate and coordinate communication associated with patient treatment and care. At the organization level, global information processing and communication can be activated by the use of ECD and BC such that electronic health summaries and patient tracking can lower the level of uncertainty and equivocality. At workgroup level, the use of RV or streamlined interface with diagnostic and therapeutic clinical units (e.g. laboratory and radiology) becomes salient so that the workgroup can collectively diagnose and create care plans for severe patients or patients with multiple comorbidities. At the individual level, local care coordination and communication by the actual users of the systems can be activated by the use of CPOE. CPOE can enhance the interface between attending physicians and the care teams and thereby automate routinized communication processes. Another significant finding of our study is the idea that impacts of EHR use differ even for the patients with varying degree of LOS. While LOS of the most extreme patients was not significantly affected by the use of EHR, the LOS of lower to upper- middle quantile patients were impacted by the different feature use of EHR.

This study has a few limitations. First, as the results are captured based on cardiac patients from California hospitals, a clear limitation is the generalizability of our results for a broader patient population. As such, it will be useful to consider the effect of EHR on the performance of hospitals in other states so that the results can be compared and cross-validated. Moreover, this study focused exclusively on patient length of stay as the outcome measure. Future research could examine the effect of EHR on alternative measures of clinical outcome such as 30-day post-operative mortality rates or the likelihood of 30-day hospital readmission.

Chapter 4

Measuring the Impacts of HIT on Emergency Department (ED) Efficiency Outcomes

4.1. Introduction

Wait time in Emergency department (ED) has long been of a concern as it hinders achieving quality and efficiency of ED care. For quality and timeliness of urgent care, ED should determine accurate care plan based on the focal patient's health needs, patient volume and available resources within the department (Ozkaynak and Brennan 2012). While organizational and operational process improvement for reducing wait time have been noted elsewhere (e.g. Hoot and Aronsky 2008), the role of EHR in ED settings is spotlighted to better accessing to patient information, automating manual tasks, standardizing orders and documentation, improving patient tracking, and facilitating communication among a multidisciplinary team (IOM 2007). In responding to such growing expectation on EHR, about 84% of EDs have used basic EHR functionality within the departments as of 2011 (National Center for Health Statistics 2015).

Despite such surge in EHR implementation rate across EDs, little is known as to whether and how EHR can reduce ED wait time (Furukawa 2011). Some notable research has largely explored direct effects of EHR on ED performance (Pallin et al. 2010, Furukawa 2011, Spellman et al. 2011, Ward et al. 2014a, Ward et al. 2014b, Ben-Assuli 2015) and indirect effects of EHR have been discussed elsewhere, limiting its focus to a mechanism of EHR-induced cross-department coordination benefits (e.g. Mekhjian et al. 2002, Husk and Waxman 2004).

The findings from literature review calls for more attention on the indirect impacts of ED-based EHR on ED performance for two reasons. First, EHR implementation is rather adding or expanding existing functionalities of ED Information Systems than creating new systems in an ED. In fact, each ED has own HIT systems prior to EHR whose functionalities ranging from physician clinical documentation, patient tracking, electronic discharge instructions and prescription support/printing (ACEP 2009, ACEP 2011). With these overlapping functionalities with EHR, focus of EHR impact study comes to change from main effect of EHR to the added-on functionalities of EHR to the existing systems. Second, EHR implementation further streamline data management and sharing capabilities within the EDs. By electronic interoperable and ubiquitous data access driven by EHR, ED-specific EHR implementation modifies, replaces and/or expands the existing information management capabilities. For these reasons, considering direct effects of EHR might be misleading and therefore, it is imperative to scrutinize this underexplored phenomenon - whether and how ED-specific EHR implementation influences ED performance, contingent upon the existing information management capabilities in an ED context.

From an information processing theoretical lens in the organization, thus, this study particularly focuses on the characteristics of the existing ED-specific information processing capability and its potential mediating impacts in the link between ED EHR and ED outcomes. The widely anticipated benefits of EHR implementation are simultaneous access to health information and sharing within and between departments. Especially in ED settings, timely access and dissemination of the related health information can help urgent care providers to make informed decision on each patient case. While prior literature has extensively studied the operational and organizational factors enhancing ED performance (e.g. Green and Kolesar 2014, Valentine and Edmondson 2015), this paper pays special attention to the ex ante technological factors that influence the link between EHR implementation in ED and ED performance. The basic tenet of this study is that EHR may directly influence the existing information management and information sharing capability and that the unobserved, existing intervention of information management capability may lead to enhanced ED performance.

To test the mediated impacts of EHR on ED performance, I combined EMS utilization data from the Office of Statewide Health Planning and Development (OSHPD) with data from American Hospital Association's EHR Adoption Survey and Healthcare Information and Management Systems Society (HIMSS) Analytics' annual survey. Then, outcome-based causal mediation analysis was employed to test the ED EHR- mediator- ED performance link and the results were verified by testing potential confounding effects. The results suggest that the ex ante ED characteristics do mediate the impacts of EHR within the department such that the mediated EHR differentially increase or reduce various measures of ED wait time. Furthermore, I found that in the first round of wait time (between first arrival and first treatment), the existing HIE capability positively mediates the link between EHR and ED wait time. Another round of wait before final disposition to either hospital admission or home, the ex ante level of clinical process integration reversely mediates in the link between EHR and ED wait time.

4.2. Theoretical Foundation

4.2.1. Information Processing View in an ED Context

Theoretical perspective on information processing view provides insight into the mediated impacts of EHR in this granular healthcare domain. Information processing theory posits that uncertainty and equivocality are two contingencies that influence how organizations process information and determine the need for coordination mechanisms (Daft and Lengel

1986). Uncertainty refers to the difference in the amount of information required to solve a problem vis-à-vis and the amount of information possessed by the decision maker (Galbraith 1977). Equivocality, on the other hand refers to the existence of multiple and conflicting interpretations about an organizational situation (Weick 1979). In contrast to uncertainty, which is definable, decomposable and solvable through objective data analysis, equivocality cannot be effectively structured (Daft et al. 1987). Therefore, uncertainty generally calls for more information to analyze whereas equivocality necessitates exchanges of views to define the problem and resolve disagreements among stakeholders. For example, patient-related uncertainty guides whether clinicians coordinate via predefined rules and scheduled meetings (i.e. programmed coordination) or via mutual adjustments on the spot (i.e. non-programmed coordination) (Argote 1982). In addition, the level of equivocality influences how managers select communication methods from simply written memos to face-to-face discussions (Daft et al. 1987).

In the healthcare context, clinical service settings in hospitals epitomize the definition of uncertainty and equivocality as discussed above. A service is in general "a performance or an effort rendered by one party for another" (p. 92, Mills and Turk 1986). The quality of the service rests on the available information in a given encounter and more importantly, the main sources of information are the stakeholders (Mills and Turk 1986). Thus, health organizations must have the capability to process idiosyncratic information coming from multiple stakeholders. For example, patients arrive at the focal hospitals with critical and/or sometimes asymptomatic conditions; physicians and the care teams have their own daily schedules and appointments at the encounters with patients; hospitals maintain their own rules and guidelines for overall patient care. In the course of care delivery, therefore, the level of uncertainty and equivocality may increase due to the paucity of patient health information that needs to be shared and interpreted as well as with the possibility for multiple interpretations. Such information processing needs become even greater in ED setting where there are unexpected volume of patients with urgent care needs and their health information does not exist. Therefore, capabilities for processing various types of health information are particularly critical in ED settings.

4.2.2. EHR and Information Processing Needs in EDs

EHR is designed to store, access, and retrieve health information from different stakeholders. The different aspects of EHR functionality can enhance hospital's information processing capability by both (1) allowing more information to be collected and shared and (2) streamlining communication among care providers. Information processing generally occurs at three distinct levels in hospitals - at the organization, the workgroup, and the individual levels. First, at an organizational level, EHR functionalities such as electronic clinical documentation (ECD), and result viewing (RV) and bar coding (BC) can enable clinicians to create the unified clinical reports that contain data such as patient demographics, test results from laboratory and radiology, and medication lists and such electronic information can be easily shared across different hospital units. Next, at a workgroup level, the use of EHR can better streamline information sharing processes among different departments via a unified system interface. In fact, result viewing (RV) is linked to laboratory and radiology department and computerized practitioner order entry (CPOE) links related care providers per a clinical order. Such EHR capabilities can automate department-to-department interactions so that diagnostic and therapeutic processes are seamlessly operated. Although paper-based charts have also delivered the aggregated information between clinical departments in hospitals, health information in the paper charts is recorded one after another such that those charts are not accessible by multiple clinicians all at once. EHR's ubiquitous and real-time attributes change how health information is created, shared, and communicated at a workgroup level. Lastly, at an individual level, the use of EHR functionalities can enhance physician's clinical decision making processes by structuring clinicians' tacit knowledge. In general, care plans for each patient depend on the sole discretion of the attending physicians. Physicians' tacit knowledge, experience and hunches are often stored in their minds (Alavi and Leidner 2001) such that it is a challenge to transform physicians' unstructured knowledge into the structured and sharable knowledge for resolving ambiguous clinical problems. As such, decision support (DS) systems can provide individual physicians with structured rules for cross-checking his or her knowledge with external information reference such as drug-drug interactions and/or external clinical guidelines. Together with personal knowledge management, accessibility to the internally-accumulated health information from multiple sources may create an environment in which physicians make clinical decisions with quality information in a timely manner. Second, we posit that EHR use can also influence inter-unit communication patterns such that all three levels of communications are simultaneously automated and streamlined. As opposed to traditional order processes, for instance, CPOE provides such an electronic interface to practitioners across different hospital units that it makes each clinical order traceable over the course of a clinical service. As electronic reports inform related care providers about what has been done and what is necessary for the next care plan, the need for ad hoc conversations among care providers can be greatly reduced. The use of the functionalities in EHR systems can therefore differentially enhance information processing capability by reducing uncertainty and equivocality across hospital units. As a result, ED can improve their clinical outcome from enhanced clinical decision-making, streamlined information sharing, and care coordination across other hospital units.

Especially in the Emergency Department (ED), insufficient information processing capability has been a reason for prolonged wait time in the course of ED care services (American College of Emergency Physicians 2004). As emergency departments (EDs) are the facilities to treat patients with urgent and life-threatening symptoms, the amount of health information at time of patient care often leads to bottleneck certain ED care processes, all of which lead to negative care outcomes such as ambulance diversion, treatment delays, and other unexpected clinical outcomes (Furuakawa 2011). Especially, ED care is largely characterized by a series of wait time and its outcomes (Asplin et al. 2003). In the first stage, patients arrive at the ED and wait until first triaged to see a doctor or leave without being seen. In the following stage, patients further wait for their disposition – whether disposed to the focal hospital or to home. Under this circumstances, ED care providers' decision making at each stage, based on limited resources availability, unexpected patient volume and insufficient information on health symptoms can increase or decrease a level of efficiency of ED care.

4.2.3. ED Efficiency Outcomes

Prior literature have widely studied various measures of efficiency of ED care including wait time and ED length of stay (e.g. Horwitz et al. 2010, Furukawa 2011, Kennebeck et al. 2011, Ward et al. 2013, Batt and Terwiesch 2015). Thus far, interdisciplinary research identified the existing coping mechanisms to improve the efficiency of ED care. For example, on the one hand, operations research suggested a number of process improvement tools for better patient throughput in the ED processes using queuing theory, supply chain management, human factors engineering, and statistical process control (IOM 2007, Green and Kolesar

2014). On the other hand, organization management literature discussed the existing care coordination to enhance ED performance such that at the level of uncertainty about patients' health conditions, different care coordination mechanisms among care providers become differentially efficient (Argote 1982, Valentine and Edmondson 2015). However, the role of EHR-induced information managing capability remained underexplored in an ED setting. In a more broad sense, IS literature carefully considers technology-driven data integration (e.g. Goodhue et al. 1992), IS-organizational process alignment (e.g. Devaraj and Kohli 2000) and information exchange (e.g. Davenport and Short 1990) as the existing mechanisms to strengthen the focal IS implementation within the organization. By extending these IS findings to an ED context, this paper contemplates the nearest IS factors that may be directly influenced by EHR implementation – ED information capability.

4.2.4. Mediated Impacts of EHR on ED Efficiency Outcomes

By the introduction of the aforementioned EHR in an ED context, ED's information capability can be more streamlined and further influence on ED performance (IOM 2007). In each stage of a patient's ED visit, successful implementation of EHR functionality such as electronic clinical documentation, result viewing, computerized practitioner order entry and clinical decision support can streamline data integration, IS-process alignment and information exchange capability. First, *as a technology capability*, the implementation of EHR can provide tight data integration, leading to continuity of care documentation in the emergency departments (HIMSS 2012). For example, the electronic patient charts enhance rapid patient entry process and it further reduces the number of patients who left without being seen (LWOBS) (Chan et al. 2005). Thus, EHR in ED can facilitate better data integration and such enhanced technological process capability may positively reduce patients' wait time. Second, *as an* *organization capability,* the implementation of EHR can trigger clinical process redesign and reduce wait time with increasing patient satisfaction (Spaite et al. 2002). Furthermore, under the HITECH Act, the integrated clinical systems with pharmacy systems and CPOE are required (HIMSS 2012). As EHR implementation can lead to clinical process integration across systems (Davidson and Chismar 2007), such integrated care process with EHR can lead to wait time reduction. Lastly, *as an information exchange capability*, EHR-enabled electronic documentation can strengthened the existing level of information exchange with other stakeholders beyond emergency department. At time of a patient's arrival, transfer, and disposition, information exchange is crucial to timeliness of ED care (Frisse et al. 2011). According to American Hospital Association's EHR Adoption survey, at least 20% of hospitals participate in information exchange within and/or out of network service providers with varying EHR functionality such as patient demographics (43%), clinical care records (20%), laboratory results (28%), medication lists (21%), radiology reports (30%) and discharge summaries (21%) (2008). One can expect that the more functionalities of EHR are implemented, the better information is expected to be exchanged with related care stakeholders.

Taken together, this study posits that EHR capability can improve ex ante ED information capability which leads to better ED performance. With specific focus on the existing capabilities of clinical data integration, clinical process integration and information exchange, this study investigates whether and how the existing ED care process capability is aligned with the functionalities of EHR and further influence wait time reduction at different stages of ED care process. Figure 9 depicts the proposed mediation model of this study.

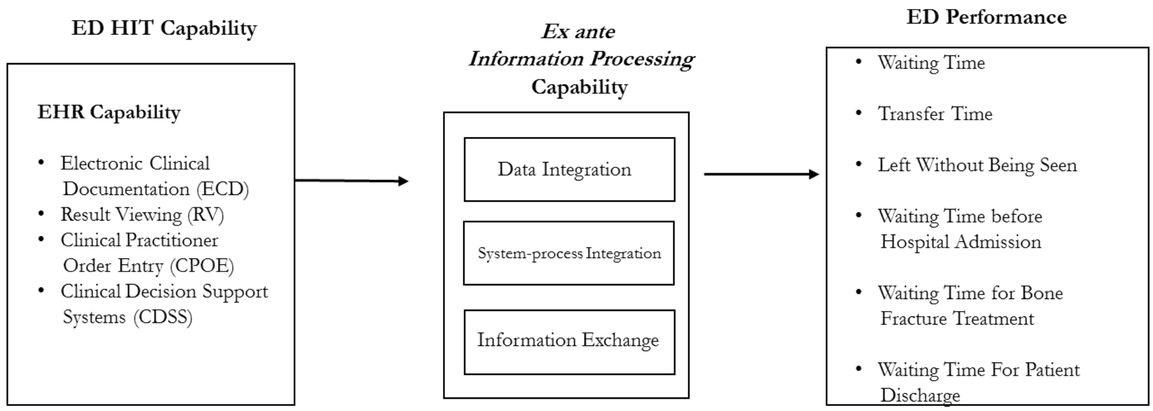


Figure 9. Research Model of the Study

4.3. Methods

4.3.1. Data Source

To test this mediation relationship among EHR- ED information capability- ED wait, multiple sources of secondary data are combined. First, data on ED utilization was obtained from the Office of Statewide Health Planning and Development (OSHPD) EMS data in California during 2009- 2013. This data includes characteristics of each hospital-based ED, patient volume and severity of health conditions, ambulance diversion, etc.. Second, data on ED performance came from CMS Hospital Compare 2013-2014. Third, data on ED electronic health record (EHR) adoption was obtained from American Hospital Association (AHA) during 2008-2010. Fourth, mediation variables were obtained from HIMSS Analytics during 2009-2013. As each data is merged with Medicare id, an initial panel data during 2009-2013 was created. Since the focal dependent variables of interest has only one year observation, I extracted one year cross-section data and the resulting sample size is 421 observations of CA hospital-based EDs in 2013.

4.3.2. Research Variables

4.3.2.1. Dependent Variables

Various measures of ED performance have been widely used in prior literature (e.g. Furukawa 2011, Valentine and Edmondson 2015, Lucas et al. 2009). This paper particularly utilized six different measures of ED performance in a course of ED care process- wait time for first treatment, time before hospital admission, wait time for boarding, wait time for bone fracture treatment, percentage of patients who left without being seen (LWOBS) and wait time for home. In fact, this paper views ED performance as a two-staged phenomenon. As shown in Figure 10, first stage spans wait time between arrival and first care provision or leaving and second stage covers between first care and the final disposition decision. In the first stage, patients arrive at the ED and wait until first triaged to see a doctor, for bone fracture treatment or left without being seen. In the following stage, patients further wait for their final disposition – whether disposed to the focal hospital or to home. This categorization of the dependent variables is particularly useful because one can see the performance benefits of ED-specific EHR implementation across different stage of ED care process. Figure 10 depicts the categorization of the six performance measures that are used in this study.

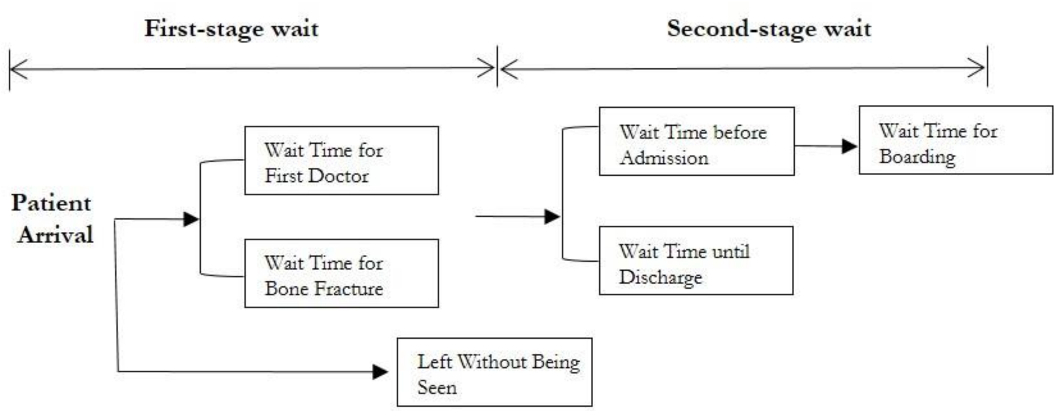


Figure 10. Categorization of Wait Time

In the first-stage wait, there are three measures of wait time that captures pre-treatment wait time- wait time for first treatment, wait time for bone fracture treatment and left without being seen. First, wait time for first treatment is measured by the total minutes patients spent in the emergency room before being seen by a doctor. Next, wait time for bone fracture treatment is total minutes of wait time for patients who came to the emergency department with broken bones had to wait before getting pain medication. Lastly, left without being seen (LWOBS) variable is measured by the percentage of patients who left the emergency department before being seen. In the second-stage wait, there are three measures to capture post-treatment wait time. First, Time before admission represents Average time patients spent in the emergency room before being admitted to the hospital. Next, Transfer time indicates how long it takes among admitted patients for being taken to their room. Lastly, Time until sent home is total wait time for patients to spend in the emergency room before being sent home. The definitions of all these variables are adopted from Center for Medicaid and Medicare Services (CMS).

4.3.2.2. Independent Variable

The independent variable of interest is ED-based EHR implementation whether a focal ED implemented specific functionality of EHR. This paper takes full advantage of rarely available American Hospital Association (AHA) information on EHR implementation in ED in terms of electronic clinical documentation, result viewing, CPOE and CDSS. With this information only provided in 2008, first, I created four EHR binary variables along with four functionalities and coded it as 1 up to 2013 if an ED implemented the focal EHR application in 2008. After counting the number of available EHR functionalities, the final independent variable is coded by a median split (1: present, 0: otherwise) if ED has above average number of EHR functionality including electronic clinical documentation, result viewing, CPOE and CDSS.

4.3.2.3. Mediator Variables

For the mediator variables, three categories of mediation variables were selected based on prior literature and practical note (e.g. Forster et al. 2003, ACEP 2009, HIMSS 2012). As the ED's existing technology capability, the existence of emergency department information system (EDIS) and CDSS data integration were operationalized. First, EDIS variable captures whether emergency department information system (EDIS) is live and operational which indicates the level of an information management in each ED. EDIS is known to process patient data distinctively in EDs and the implementation of EHR functionality can further influence the process of patient entry/tracking, clinical documentation, CPOE, result reporting, discharge management as well with administrative functions (ACEP 2009). Next, CDSS data integration captures whether medical content data is integrated into clinical decision support tools or decision alerts for clinicians. This variable indicate how clinical data is integrated with CDSS alerts and recommendation. Second, in terms of ED organizational capability, CDSS-supported clinical processes and nursing- CPOE-pharmacy process integration were chosen (HIMSS 2012). On the one hand, CDSS-supported clinical process integration shows how CDSS provides care guidelines for physicians and nurses, system alerts for drug dosing and drug interactions with drug/drug, drug/lab, or drug/food. On the other hand, nursing-CPOE-pharmacy process captures whether the electronic medication administration records (EMAR) is simultaneously integrated with pharmacy and CPOE. Under the HITECH Act, it is required to demonstrate the data/process integration with EMAR- CPOE- Pharmacy which has been major forces to replacing pharmacy systems

(HIMSS 2012). Lastly, for measures of ED environment capability, health information exchange with hospitals within hospital network and with ambulatory providers out of hospital network were selected. Each ED has existing information exchange guidelines and these information sharing rules can be influenced by EHR's electronic health information sharing capability (Frisse et al. 2012). Table 15 presents the definition and operationalization of mediator variables.

Table 15. Definition and Operationalization of Mediator Variables

Category	Variable Name	Operationalization	Data Source
Technology Level	EDIS	EDIS system implementation (binary)	HIMSS Analytics
	CDSS Data Integration	The medical content data is integrated into workflow applications as clinical decision support tools or decision alerts for clinicians	
Organization Level	CDSS-supported Clinical Process Integration	• Clinical guidelines and pathways for nurses • Clinical guidelines and pathways for physicians • Drug dosing interactions • Drug interactions (drug/drug, drug/lab, drug/food	
	Nursing- EHR-Pharmacy Process Integration	Whether the EMAR is integrated with pharmacy and CPOE	
Information Exchange Level	Health Information Exchange	HIE with ambulatory provider outside of hospital network	AHA EHR Adoption Survey
		HIE with hospitals in a network	

4.3.2.4. Control Variables

This paper includes a number of key covariates at ED level, hospital level and county level as potential confounding variables in the mediation relationships between ED EHR- ED information capabilities – ED wait. At ED level, type and size of ED facility, patient symptoms and past experience with ambulance diversion were included that are known to influence ED wait time (e.g. Argote 1982, Kennebeck et al. 2011, Furukawa 2011). First, ED facility type captures a level of urgent care readiness – whether a hospital is staffed and equipped at all times to provide prompt care for any patient presenting urgent medical problems. ED size is measured by the total number of ED stations. Next, a proportion of ED visit which requires a problem focused history/examination, and straightforward medical decision making based on severity of symptoms- minor, moderate, severe without life threat, and severe with life threat. Lastly, ambulance diversion is included to capture whether a focal emergency department is generally crowded. At hospital level, covariates that are known to influence hospital performance such as hospital age, hospital ownership (profit vs. not-for-profit), urban location and health service area were included. Lastly, at county level, I include covariates that are related to ED's market competition and county population characteristics. ED market competition can be related to the adoption, selection, and utilization of EHR in the location and this variable is measured by the total number of retail clinics in the county (RAND 2010). For the county characteristics, I include the proportion of population aged over 65 and median household income. Table 16 presents the definition and operationalization of control variables in details.

Table 16. Definition and Operationalization of Control Variables

Category	Variable Name	Definition	Operationalization
ED Level	ED Basic Facility	Basic ED provides emergency medical care in a specifically designated part of the hospital that is staffed and equipped at all times to provide prompt care for any patient presenting urgent medical problems	Binary
	ED Size	Total number of ED stations	Count
	ED Patient Visit Types: Minor Symptom	A proportion of ED visit which requires a problem focused history/examination, and straightforward medical decision making	minor symptom visits/total ED visits*100
	ED Patient Visit Types: Moderate Symptom	A proportion of ED visit that requires an expanded problem-focused history/examination, and medical decision-making of moderate complexity	Moderate symptom visits/total ED visits*100
	ED Patient Visit Types: Severe Symptom	A proportion of ED visit which requires a comprehensive history/examination, and medical decision-making of high complexity	Severe with threat symptom visits/total ED visits*100
	ED Patient Visit Types: Severe Symptom without life threat	A proportion of ED visit that requires a detailed history/examination, and medical decision-making of moderate complexity. Usually, the presenting problems require urgent evaluation by the physician but do not pose an immediate threat to life or physiologic function	Severe without threat symptom visits/total ED visits*100
	Ambulance Diversion (Binary)	Whether a hospital closed its Emergency Department to ambulances and resulted in ambulances being diverted to other hospitals	Binary 1= Yes 0= No
Hospital Level	Hospital Age	Hospital age	Continuous
	Ownership	Profit vs. not-for-profit hospital	Categorical

	Urban Location	Urban (binary=1) vs. rural location	Binary
	Health Service Area	A geographic region based on geographic features, political boundaries, population, and health resources, for the effective planning and development of health services (Categorical)	Categorical
County Level	Market Competition	The total number of retail clinics and urgent care facilities in the county	Count
	Population Characteristics	Proportion of Population over 65	Percentage
		Median Household Income ($)	Continuous

4.4. Empirical Analysis

To test the mediated impacts of EHR in an ED context, causal mediation analysis with potential outcomes framework was employed (Rubin 1974, Pearl 2001, Jo 2008, Sobel 2008, Imai et al. 2010a, Imai et al. 2010b, for the description of this study, see Linden and Karlson 2013). Typically in an outcome-based mediation framework, for a treatment variable with condition of $T_i = 1$ or the control $T_i = 0$ for observation i, the outcome for observation i in the treatment condition is denoted as$Y_i(T_i)$. As each observation has only one condition such that one cannot generally observe unit-level treatment effect, main focus of estimation in this context is to be the average treatment effect. More specifically, in a mediation approach proposed by Imai et al. (2010), outcome for observation i under the treatment status $T_i = t$ is $Y_i\{T_i, M_i(T_i)\}$ and counterfactual potential outcome is then calculated per each observation to estimate causal mediation effect (Hicks and Tingley 2011). The three quantities of causal mediation analysis are for each treatment status t=0 or 1 are

Average Causal Mediation Effect (ACME) = $Y_i\{t, M_i(1)\} - Y_i\{t, M_i(0)\}$

Average Direct Effect (ADE) = $Y_i\{1, M_i(t)\} - Y_i\{0, M_i(t)\}$

Total Effect (Average Treatment Effect) = $Y_i\{1, M_i(1)\} - Y_i\{0, M_i(0)\}$

However, the identification of the causal mediation effects is complicated that a potential outcome for measuring indirect and direct effects is never observed. Thus, Imai et al. (20010b) proposed sequential ignorability[5] assumption and under this assumption, when mediator M and outcome variables Y are continuous, the mediation model is equivalent to fitting two regressions for treatment variable T and covariates X.

$$M_i = \alpha_1 + \beta_1 T_i + \gamma_1 X_i + \epsilon_{i1} \qquad \text{- (1)}$$

$$Y_i = \alpha_2 + \beta_2 T_i + \delta M_i + \gamma_2 X_i + \epsilon_{i2} \quad \text{- (2)}$$

4.5. Results

First, Table 17 and 18 depict descriptive statistics and correlations, respectively. The average wait time for first treatment is 21.53 minutes and about 1% of patients who visited the ED left without being seen in the sample in 2013. The adoption of EHR indicates that 37% of ED implemented some components of EHR functionality across ECD, RV, CPOE and CDSS. The correlation table in Table 2 reports direction and magnitude of correlation among variables are within range. For the mediation analysis, all dependent variables of this study are all log-transformed.

[5] More explanation on sequential ignorability can found at Imai et al. (2010).

Next, from Table 19 to Table 21, results on the mediated impacts of EHR on each dependent variable are presented. I report average causal mediation effect (ACME), average direct effect (ADE), and total effect (average treatment effect) from the two regressions in equation (1) and (2) and such results are validated by sensitivity analysis by using medsens commands in STATA (Hicks and Tingley 2011). Although there is no clear-cut threshold of the correlation value ρ (Imai et al. 2010b), relatively higher correlation among residuals indicate that the observed mediated effect may not be due to unobserved confounding variables. This paper uses ρ =0.1 as a threshold value to validate the results from causal mediation analysis[6].

[6]Imai et al, (2010b) provided sensitivity analysis guideline to see whether the results obtained from causal mediation analysis can be modified by the potential correlation between residuals, measured by the correlation between ϵ_i1and ϵ_i2 (or Rho) at ACME=0. Sensitivity analysis presents that the level of vulnerability of the observed mediated effect at the presence of unobserved confounding variables. Results from sensitivity analysis is in appendix I.

Table 17. Descriptive Statistics

Variable Name	Obs	Mean	SD	Min	Max
Wait time for first treatment(Minutes)	421	21.53	30.56	0	315
Time for boarding (Minutes)	421	71.43	87.93	0	445
LWOBS (%)	421	0.01	0.02	0	0.17
Time for hospital admission (Minutes)	421	167.11	183.42	0	874
Time for bone fracture (Minutes) treatment(Minutes)	421	29.95	33.72	0	128
Time for home (Minutes)	421	81.29	86.69	0	331
EDIS (Binary)	421	0.78	0.41	0	1
CDSS data integration (Binary)	421	0.28	0.45	0	1
Nursing_CPOE_Pharmacy integration (Binary)	421	0.36	0.48	0	1
CDSS process integration (out of four)	421	2.09	1.62	0	4
HIE with out of network ambulatory provider	421	0.43	0.50	0	1
HIE with in-network hospital	421	0.30	0.46	0	1
ED_based EHR (Binary)	421	0.37	0.48	0	1
Basic ED (Binary)	421	0.63	0.48	0	1
% Minor Symptom in ED visits	421	4.20	7.35	0	40.0799
% Moderate Symptom in ED visits	421	26.37	19.41	0	71.5696
% Severe Symptom without threat in ED visits	421	17.60	13.20	0	49.67
% Severe Symptom with threat in ED visits	421	11.78	13.57	0	100
Ambulance Diversion (Yes/No)	421	0.34	0.47	0	1
Hospital age	416	30.32	32.32	0	156
Hospital ownership	421	3.44	3.16	0	9
Urban location (binary)	421	0.23	0.42	0	1
Health Service Area (HSA)	421	5.52	5.14	0	14
ED size (# of ED station)	421	16.33	16.52	0	106
# of Retail clinics in a county	421	5.74	9.88	0	40
% of County population over 65 years old	421	0.11	0.05	0	0.233
County median household income ($)	421	48090.05	24161.66	0	91195

Table 18. Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	Wait time																											
2	Transfer time	0.21																										
3	LWOBS	0.49	0.12																									
4	Time before admission	0.14	0.13	0.12																								
5	Broken bone	0.12	0.22	0.14	0.01																							
6	Time for home	0.00	0.02	-0.07	0.00	0.17																						
7	EDIS	-0.03	0.00	-0.01	-0.04	-0.04	-0.01																					
8	ED occupancy	-0.11	0.10	-0.06	0.09	-0.09	-0.01	0.06																				
9	CDSS data inte	0.14	0.02	0.13	0.10	0.04	0.17	0.10	-0.09																			
10	Clinical process integration	-0.06	-0.01	-0.05	-0.13	-0.06	-0.08	0.14	-0.11	0.33																		
11	CDSS integration	0.05	0.14	-0.02	0.08	-0.06	0.06	0.17	-0.04	0.58	0.48																	
12	HIE out network	-0.04	0.11	-0.09	-0.02	-0.08	0.03	0.00	0.09	0.04	0.11	0.15																
13	HIE with network	-0.08	0.09	-0.17	-0.03	-0.10	-0.03	0.04	0.04	0.07	0.19	0.21	0.55															
14	ED EHR	0.06	0.15	-0.01	0.03	0.02	-0.10	0.13	-0.03	0.20	0.15	0.27	0.37	0.47														
15	ED type	0.03	0.10	-0.01	-0.06	0.07	0.10	0.04	0.03	0.09	-0.03	0.16	0.02	-0.08	-0.03													
16	Minor symptom	0.14	0.01	0.13	0.11	-0.16	-0.13	-0.05	0.03	-0.18	-0.11	-0.20	0.09	0.05	0.04	-0.17												
17	Moderate symptom	-0.17	0.13	-0.14	-0.15	-0.09	0.02	-0.06	0.16	-0.02	-0.15	-0.04	0.03	0.02	0.14	0.10	-0.29											
18	Severe w/o threat	-0.10	0.09	-0.17	0.02	0.10	0.14	0.09	-0.06	0.08	0.27	0.21	0.19	0.09	0.09	0.04	-0.26	-0.02										
19	Severe w/ threat	0.05	-0.14	0.13	0.02	0.09	0.09	0.10	-0.06	0.19	0.17	0.17	-0.15	-0.05	-0.12	-0.05	-0.18	-0.66	-0.09									
20	Diversion	0.02	0.12	0.08	-0.02	-0.08	0.00	-0.02	-0.18	0.04	0.14	-0.07	-0.05	0.04	-0.10	0.05	0.09	-0.13	0.07	0.07								
21	Hospital age	0.24	0.15	0.12	0.03	0.09	-0.02	-0.01	0.03	0.12	-0.05	0.11	0.14	-0.02	0.17	-0.12	0.20	-0.03	-0.04	-0.14	-0.01							
22	Hospital ownership	-0.11	-0.06	-0.23	0.08	-0.13	0.13	0.08	-0.11	0.15	0.01	0.21	0.25	0.20	0.09	0.02	-0.13	0.06	0.15	-0.03	0.06	-0.03						
23	Urban	-0.13	-0.01	-0.14	0.01	-0.08	0.07	-0.02	0.01	0.01	-0.03	0.03	0.11	0.13	0.02	-0.09	-0.13	0.22	0.04	-0.16	-0.22	0.01	0.26					
24	HSA	0.09	0.02	0.07	0.10	0.02	0.07	0.02	0.05	0.08	-0.03	-0.08	0.00	-0.01	0.04	-0.02	0.05	-0.05	-0.02	0.10	0.26	0.11	0.19	-0.22				
25	ED size	0.17	0.34	0.20	0.20	0.07	0.08	0.11	-0.22	0.38	0.13	0.34	0.19	0.17	0.26	0.03	-0.07	0.07	0.11	-0.04	0.17	0.18	0.21	0.00	0.23			
26	# Retail clinics	-0.02	0.03	0.05	0.05	-0.10	0.06	0.01	0.05	-0.06	0.02	0.02	0.03	0.14	0.00	-0.23	0.11	-0.11	0.03	0.07	0.29	0.06	0.08	0.00	0.15	0.15		
27	age_over_65	-0.04	-0.03	-0.13	-0.25	-0.03	-0.10	0.04	-0.17	-0.07	0.03	0.05	0.17	0.23	0.16	0.03	-0.01	0.11	0.04	-0.15	-0.15	-0.10	0.11	0.08	-0.41	-0.14	-0.12	
28	med_hincome	-0.07	0.03	-0.05	-0.19	-0.08	-0.12	0.00	-0.16	-0.07	0.16	0.08	-0.10	-0.02	-0.05	-0.01	0.05	-0.01	0.02	-0.07	0.30	-0.08	-0.10	-0.18	-0.05	-0.04	0.10	0.21

4.5.1. Mediation Relationship between EHR-ED Mediator-First Stage Wait Time

First, Table 22 – Table 24 reports average mediation effect, direct effect and average treatment effects per each dependent variables together with 95% of confidence intervals. In Table O, the mediated effect of EHR on wait time for first treatment is likely to increase wait time when data integration and clinical process integration capabilities are influenced by EHR in Table 22. Interestingly, however, average direct effect of EHR was greater than average mediation effect and both ADE and total effect (or average treatment effect) appears to reduce wait time for first treatment as a whole. This result is in line with Furukawa (2011)'s findings that fully functional EHR is shown to reduce wait time for diagnosis and treatment in the first stage of wait time. Next, for the model of wait time for bone fracture treatment, the impact of EHR on wait time for bone fracture is mediated by clinical process integration and HIE capabilities. While no direct impacts of EHR on LWOBS are noted in prior literature (Furukawa 2011), this paper identifies indirect impacts of EHR on LWOBS that if information exchange capability is enhanced by EHR, the proportion of patients who leave without any treatment is likely to decrease. Overall, in the initial stage between patient arrival and first treatment, HIE-mediated EHR is consistently associated with wait time reduction.

Table 19. Causal Mediation Results on Wait Time for First Treatment

	DV: Log(Wait Time for First Treatment)								
	Independent Variable: EHR in ED (Binary)								
	Mediation effect			Direct effect			Total effect		
Mediator	Mean	95% CI		Mean	95% CI		Mean	95% CI	
EDIS	0.009	-0.010	0.042	-0.052	-0.272	0.157	-0.043	-0.260	0.161
CDSS data integration	0.030	-0.014	0.087	-0.073	-0.289	0.133	-0.043	-0.263	0.156
EMAR-CPOE- Pharm Integration	0.012	-0.015	0.051	-0.055	-0.274	0.154	-0.043	-0.259	0.158
CDSS supported clinical process integration	0.043	0.003	0.099	-0.086	-0.305	0.123	-0.042	-0.262	0.160
HIE_ambulatory provider	-0.001	-0.030	0.026	-0.043	-0.253	0.160	-0.045	-0.254	0.154
HIE_hospital in a network	-0.047	-0.130	0.023	-0.043	-0.253	0.160	-0.090	-0.290	0.106

* All models are validated by sensitivity analysis and at the threshold of ρ=0.1, only highlighted results seem robust to the possibility of confounding factors.

Table 20. Causal Mediation Results on Wait Time for Bone Fracture Treatment

	DV: Log (Wat Time for Bone Fracture Treatment)								
	Independent Variable: EHR in ED (Binary)								
	Mediation effect			Direct effect			Total effect		
Mediator	Mean	95% CI		Mean	95% CI		Mean	95% CI	
EDIS	-0.020	-0.082	0.017	0.248	-0.073	0.554	0.228	-0.097	0.540
CDSS data integration	0.006	-0.058	0.068	0.223	-0.102	0.533	0.229	-0.097	0.537
EMAR-CPOE- Pharm Integration	-0.003	-0.054	0.040	0.231	-0.090	0.538	0.229	-0.091	0.534
CDSS supported clinical process integration	-0.062	-0.154	0.003	0.291	-0.033	0.599	0.229	-0.096	0.544
HIE_ambulatory provider	-0.016	-0.069	0.022	0.228	-0.077	0.523	0.213	-0.093	0.500
HIE_hospital in a network	-0.094	-0.224	0.008	0.228	-0.077	0.523	0.134	-0.161	0.420

* All models are validated by sensitivity analysis and at the threshold of ρ=0.1, only highlighted results seem robust to the possibility of confounding factors.

Table 21. Causal Mediation Results on Left Without Being Seen (LWOBS)

	DV: Log (Left Without Being Seen, LWOBS)								
	Independent Variable: EHR in ED (Binary)								
	Mediation effect			Direct effect			Total effect		
Mediator	Mean	95% CI		Mean	95% CI		Mean	95% CI	
EDIS	0.010	-0.015	0.047	0.039	-0.192	0.259	0.049	-0.178	0.264
CDSS data integration	0.016	-0.014	0.060	0.033	-0.198	0.254	0.050	-0.180	0.264
EMAR-CPOE- Pharm Integration	-0.010	-0.055	0.021	0.060	-0.173	0.281	0.049	-0.183	0.272
CDSS supported clinical process integration	0.001	-0.054	0.052	0.049	-0.187	0.274	0.050	-0.186	0.270
HIE_ambulatory provider	0.013	-0.014	0.053	0.049	-0.171	0.262	0.062	-0.158	0.273
HIE_hospital in a network	-0.103	-0.201	-0.028	0.049	-0.171	0.262	-0.054	-0.263	0.154

* All models are validated by sensitivity analysis and at the threshold of ρ=0.1, only highlighted results seem robust to the possibility of confounding factors.

4.5.2. Mediation Relationships between EHR-ED Mediator-Second Stage Wait Time

Next, Table 22 – Table 24 report causal mediation results from the second stage of ED wait time –wait time for boarding, time for hospital admission and time for home. First, a model of boarding time indicates that while some mediation effects are noted, such effects are quite vulnerable to the presence of confounding factor (see the Appendix I for sensitivity results). This might be that in the process between decision on hospital admission and room boarding, other mediation mechanisms can be more effective than ED information capability to influence the link between EHR and ED performance. For example, in practice, inpatient nursing, housekeeping, and administrative strategy are closely associated with reducing boarding time (Lucas et al. 2009). In Table 23 with dependent variable of time for hospital admission, EHR effect throughout clinical process integration is associated with reduction in wait time for hospital admission. Lastly, when patients are finally discharged to home, if clinical data integration is enhanced by EHR, such mediated effect of EHR is shown to increase wait time for sending home. However, both direct effects and average treatment effects of EHR home are associated with reduction in wait time for home.

Table 22. Causal Mediation Results on Wait Time for Boarding

	DV: Log (Wait Time for Boarding)								
	Independent Variable: EHR in ED (Binary)								
	Mediation effect			Direct effect			Total effect		
Mediator	Mean	95% CI		Mean	95% CI		Mean	95% CI	
EDIS	-0.009	-0.055	0.018	0.128	-0.167	0.409	0.120	-0.176	0.407
CDSS data integration	-0.035	-0.108	0.015	0.155	-0.143	0.439	0.120	-0.180	0.409
EMAR-CPOE- Pharm Integration	-0.013	-0.070	0.028	0.133	-0.164	0.416	0.120	-0.177	0.405
CDSS supported clinical process integration	0.046	-0.020	0.123	0.075	-0.225	0.362	0.121	-0.178	0.394
HIE_ambulatory provider	0.006	-0.030	0.048	0.120	-0.161	0.391	0.126	-0.155	0.393
HIE_hospital in a network	0.007	-0.097	0.110	0.120	-0.161	0.391	0.127	-0.137	0.387

* All models are validated by sensitivity analysis and at the threshold of ρ=0.1, only highlighted results seem robust to the possibility of confounding factors.

Table 23. Causal Mediation Results on Wait Time for Hospital Admission

	DV: Log (Wait Time for Hospital Admission)								
	Independent Variable: EHR in ED (Binary)								
	Mediation effect			Direct effect			Total effect		
Mediator	Mean	95% CI		Mean	95% CI		Mean	95% CI	
EDIS	-0.008	-0.048	0.013	0.052	-0.187	0.279	0.043	-0.197	0.276
CDSS data integration	0.011	-0.035	0.058	0.033	-0.209	0.264	0.044	-0.198	0.271
EMAR-CPOE- Pharm Integration	-0.037	-0.100	0.001	0.081	-0.157	0.307	0.043	-0.202	0.285
CDSS supported clinical process integration	0.015	-0.041	0.073	0.029	-0.215	0.263	0.044	-0.201	0.267
HIE_ambulatory provider	-0.012	-0.052	0.014	0.043	-0.184	0.263	0.031	-0.196	0.245
HIE_hospital in a network	-0.015	-0.101	0.067	0.043	-0.184	0.263	0.029	-0.187	0.242

* All models are validated by sensitivity analysis and at the threshold of ρ=0.1, only highlighted results seem robust to the possibility of confounding factors.

Table 24. Causal Mediation Results on Wait Time for Home

	DV: Log (Wait Time for Home Discharge)								
	Independent Variable: EHR in ED (Binary)								
	Mediation effect			Direct effect			Total effect		
Mediator	Mean	95% CI		Mean	95% CI		Mean	95% CI	
EDIS	-0.004	-0.034	0.016	-0.046	-0.256	0.155	-0.050	-0.260	0.153
CDSS data integration	0.035	-0.002	0.087	-0.084	-0.295	0.118	-0.049	-0.261	0.146
EMAR-CPOE- Pharm Integration	-0.011	-0.053	0.017	-0.038	-0.249	0.164	-0.049	-0.261	0.155
CDSS supported clinical processes	-0.005	-0.060	0.044	-0.044	-0.259	0.162	-0.049	-0.263	0.151
HIE_ambulatory provider	0.003	-0.023	0.032	-0.050	-0.249	0.144	-0.047	-0.246	0.144
HIE_hospital in a network	-0.031	-0.110	0.037	-0.050	-0.249	0.144	-0.081	-0.272	0.106

* All models are validated by sensitivity analysis and at the threshold of ρ=0.1, only highlighted results seem robust to the possibility of confounding factors.

In summary as shown in Table 25, causal mediation analysis found that ED-based EHR has potential to enhance efficiency of ED care and yet its impacts vary across dependent variables and mediation mechanisms. Specifically, in the first stage of patients' wait in EDs, the existing health information exchange with other healthcare organizations does mediate the relationship between EHR and ED wait time in a desired direction. In the second stage of patients wait for final disposition, despite data integration and clinical process integration intervene the performance effects of EHR, such mediated effects are greatly varied along with measures of ED wait time.

Table 25. Summary of Findings

Category	Hypothesized Relationships	Average Direct Effect	Average Causal Mediation Effect	Average Treatment Effect	Explanations
First-stage Wait Time	EHR - Wait Time	(-)	(+)	(-)	EHR implementation in ED reduces waiting time but data integration and clinical process integration-mediated EHR increases wait time.
	EHR - Broken Bone	(+)	(-)	(+)	EHR implementation in ED increase time for broken bone treatment but clinical process integration and HIE mediating factors reduce such effects
	EHR - LWOBS	(+)	(-)	(-)	EHR implementation in ED increase % of LWOBS but HIE-mediated EHR is shown to reduce the percentage of LWOBS
Second-stage Wait Time	EHR - Transfer Time		No effect		n/a
	EHR - Wait Time Before Admission	(+)	(-)	(+)	EHR is likely to increase wait time for hospital admission but clinical process integration-enhanced EHR is shown to reduce wait time before admission
	EHR - Time Until Sent Home	(-)	(+)	(-)	EHR is likely to reduce wait time for patient discharge but clinical data integration-mediated EHR is shown to increase time for patient discharge

4.6. Discussion and Conclusion

The purpose of this study is to investigate mediated impacts of EHR on various measures of ED performance. Given that the complexity of urgent care occurred in emergency departments, this study specifically focuses on the existing mediation mechanisms that can be encouraged/streamlined by the introduction of EHR and explores the relationship of EHR-mediator-ED performance. Using one year cross-section data obtained from California ED and AHA EHR adoption data, the findings suggested that the existing mediation mechanisms greatly mediate the relationships between EHR and ED performance. In the initial duration of wait time, if EHR functionality is streamlined with existing HIE capability then reduction in wait time for first treatment is noted. Furthermore, in the later stage of wait in the ED, existing data/clinical process integration selectively influences wait time for final disposition. Overall, across different measures of ED performance and mediation mechanisms, the mediated effects of EHR are differentially present. While prior literature has examined main effects of EHR on efficiency and quality of care in ED, this is one of the first studies to investigate indirect effects of ED-specific EHR on various measures of ED performance.

The results from this study suggest that the mediated benefits of EHR are only realized under certain mediating conditions and this might one of the major reasons why there have been inconclusive results on EHR impacts. Findings from this study suggested that in ED settings, EHR functionalities have potentials to streamline data gathering, managing and exchanging from urgent patients without previous health information records. However, EHR influences rather indirectly than directly when there are the existing data management, clinical care processes and information exchange patterns. If EHR-driven changes in existing mediating mechanisms can be well aligned with EHR functionalities, then reduction in selective measures of wait time is expected. Without reasonable consideration on such contextual intervening effects, measuring direct effect of EHR on efficiency of ED care might be misleading.

This study also speaks to healthcare practitioners and policy makers. Demonstrating meaningful selection and implementation of EHR among eligible healthcare organizations need to further consider how EHR features and functionalities are aligned with department level capability and necessity such as distinct urgent patient care units. Current suggestions about EHR implementation might be too standardized so that healthcare organizations with distinctive characteristics (e.g. pediatrics, psychiatrics) might face challenges to incorporate their site-specific issues with EHR implementation. American College of Emergency Physicians (ACEP) also commented that meaningful use of HIT incentives overlooked the impact of deploying EHR and other HIT in the emergency department (ED). Thus, healthcare policy makers need to further consider multi-faceted impacts of EHR implementation at multiple level of healthcare organizations as well.

Finally, this study is not without limitations. First, although causal mediation analysis was employed and validated by sensitivity analysis, the results from this study should be interpreted with caution as there might be another unobserved confounders in the relationship between EHR- mediator- ED outcomes. Traditional structural equation modeling (SEM) framework might be a good approach to further validate the findings of this study. Second, I only included some selective measures of mediator variables. Adding more comprehensive list of variables and investigating the concurrent effects on the mediated impacts of EHR can be fruitful. Lastly, I use cross-section data subsampled from California ED panel during 2009-2013 as outcome variable has only one year observation. Revisiting the research model with longitudinal data can provide further insight on how the existing conditions of ED can differentially mediate the link between EHR and ED performance.

Chapter 5

Conclusion

Through the three essays, my dissertation seeks to examine the impacts of Health Information Technology (HIT) on hospital performance. I particularly address questions about the implications of electronic health records (EHR) as an important type of HIT, at multiple levels of a hospital –at individual level, at group level, and at hospital level. The three essays in my dissertation complement each other aimed toward building a holistic understanding of the performance impacts of EHR. Throughout this dissertation work, a careful consideration of the context in which EHR is implemented and utilized allows me to rigorously pursue the causal claims of the HIT impacts in a healthcare context. Overall, my dissertation research involves the examination of critical phenomena in the healthcare domain and contributes to HIT research by drawing the interdisciplinary research community's attention to this ongoing discussion.

Distinct from other research, this dissertation carefully puts the existing contextual factors first and actively investigates the indirect impacts of EHR on various measures of hospital performance at each level. The three essays of my dissertation found that collectively, the adoption and implementation of EHR have great potential to improve hospital performance at multiple levels of a hospital. However, EHR implementation was differentially influenced by idiosyncratic contextual characteristics at each level. While a hospital's *ex ante* technical, organizational and environmental complementarity can be meaningful indicators for further predicting healthcare organizations' readiness for Meaningful Use of HIT within the hospitals and building accountability of care and health information infrastructure across healthcare, the impacts of EHR are only found at some measures under the certain conditions. This might be the main reason for inconclusive results in some HIT impact research and therefore, with caution, I propose that EHR impacts might be a local phenomenon at the moment. Practically, such results imply that, in order for the enhanced healthcare outcome and performance, healthcare policy makers need to concurrently reevaluate the existing HIT capability and contextual characteristics. In other words, more detailed EHR implementation guidelines might be necessary for the US hospitals and eligible professionals across EHR functionality, across existing characteristics of healthcare organizations (e.g. ownership types, specialty and size and location), and across patient heterogeneity. More customized EHR implementation guidelines would accelerate the success of EHR implementation and lead to the desired outcomes from it across US healthcare organizations.

In future research, I will continue to look at the roles of various types of HIT innovation over and beyond organizational boundaries. EHR technologies link all healthcare stakeholders together and seamless transmission of the electronic health information changes the healthcare horizons- the relationships between hospitals and physician practices, hospitals and patients, and even patients and personal health records (PHR) vendors. My future research will consider such fast-growing and fast-changing HIT impacts at a more granular level.

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Appendix I. Results from Sensitivity Analysis

	DV: Log(Wait Time for First Treatment)		
	Independent Variable: EHR in ED (Binary)		
	Sensitivity Analysis		
Mediator	Rho	R square for mediator and outcome	R square for residual and total variance
EDIS	0.0746	0.0056	0.0044
CDSS data integration	0.2106	0.0444	0.0288
EMAR-CPOE- Pharm Integration	0.1217	0.0148	0.0105
CDSS supported clinical process Integration	0.1747	0.0305	0.0184
HIE_ambulatory provider	-0.0064	0	0
HIE_hospital in a network	-0.079	0.0062	0.0027

* Rho represents correlation between residuals in equation (1) and equation (2) in chapter 4.

	DV: Log (Wait Time for Bone Fracture Treatment)		
	Independent Variable: EHR in ED (Binary)		
	Sensitivity Analysis		
Mediator	Rho	R square for mediator and outcome	R square for residual and total variance
EDIS	-0.0773	0.0060	0.0050
CDSS data integration	0.0109	0.0001	0.0001
EMAR-CPOE- Pharm Integration	-0.0142	0.0002	0.0001
CDSS supported clinical process Integration	-0.1337	0.0179	0.0106
HIE_ambulatory provider	-0.0583	0.0034	0.0017
HIE_hospital in a network	-0.1157	0.0134	0.0062

	DV: Log (Left Without Being Seen, LWOBS)		
	Independent Variable: EHR in ED (Binary)		
	Sensitivity Analysis		
Mediator	Rho	R square for mediator and outcome	R square for residual and total variance
EDIS	0.0679	0.0046	0.0034
CDSS data integration	0.0782	0.0061	0.0038
EMAR-CPOE- Pharm Integration	-0.0537	0.0029	0.0019
CDSS supported clinical process Integration	-0.001	0	0
HIE_ambulatory provider	0.08	0.0064	0.0031
HIE_hospital in a network	-0.1889	0.0357	0.0161

	DV: Log (Wait Time For Hospital Admission)		
	Independent Variable: EHR in ED (Binary)		
	Sensitivity Analysis		
Mediator	Rho	R square for mediator and outcome	R square for residual and total variance
EDIS	-0.0626	0.0039	0.0032
CDSS data integration	0.0314	0.001	0.0007
EMAR-CPOE- Pharm Integration	-0.1636	0.0268	0.0186
CDSS supported clinical process Integration	0.0352	0.0012	0.0007
HIE_ambulatory provider	-0.063	0.004	0.002
HIE_hospital in a network	-0.0218	0.0005	0.0002

	DV: Log (Time For Home)		
	Independent Variable: EHR in ED (Binary)		
	Sensitivity Analysis		
Mediator	Rho	R square for mediator and outcome	R square for residual and total variance
EDIS	-0.0342	0.0012	0.001
CDSS data integration	0.1272	0.0162	0.0115
EMAR-CPOE- Pharm Integration	-0.0587	0.0034	0.0025
CDSS supported clinical process Integration	-0.0178	0.0003	0.0002
HIE_ambulatory provider	0.0208	0.0004	0.0002
HIE_hospital in a network	-0.0589	0.0035	0.0017

	DV: Log (Wait Time for Boarding)		
	Independent Variable: EHR in ED (Binary)		
	Sensitivity Analysis		
Mediator	Rho	R square for mediator and outcome	R square for residual and total variance
EDIS	-0.0522	0.0027	0.0021
CDSS data integration	-0.0961	0.0092	0.0061
EMAR-CPOE- Pharm Integration	-0.0485	0.0024	0.0016
CDSS supported clinical process Integration	0.0922	0.0085	0.0048
HIE_ambulatory provider	0.0292	0.0009	0.0004
HIE_hospital in a network	0.014	0.0002	0.0001