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Health Information Technology and its Impact on Health Services Use and Quality

By
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Doctor of Philosophy

Health Services Research and Health Policy

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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
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in Health Services Research and Health Policy

2014

Abstract

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Health information technology, including electronic health records, has the potential to improve healthcare quality and outcomes by innovating healthcare delivery processes. This dissertation is comprised of three essays investigating the impact of Electronic Health Records (EHRs) on health services utilization and quality of healthcare both in ambulatory and hospital care settings.

The first essay examines the impact of eight EHR components that map four core EHR functionalities on the frequency of health behavior counseling provided during primary care visits. This essay finds that two functionalities, order entry and health information and data, were independently associated with increases in the probability of health behavior counseling service delivery. On the other hand, decision support and results management were associated with decreases in the provision of health behavior counseling services when these components were used alone. However, using these two functionalities with relevant complementary components increases health counseling services.

The second essay examines differential impacts of EHRs on hospital-acquired adverse patient safety events depending on intra-operability of an EHR system and the degree of physician resistance. The main conclusion of this essay is that a single source EHR system is associated with a reduction in patient safety events.

The third essay examines whether EHRs enhance adherence to 3 core Surgical Care Improvement Project (SCIP) infection-prevention process of care measures and reduce postoperative infections. The results show that hospitals with basic EHRs are more likely to adhere to SCIP infection-prevention measures, and an increase in adherence rates of one of the 3 core SCIP measures, timely start of antibiotics, are associated with lower postoperative infection rates. However, the results finds no significant mediation effect of SCIP process of care measures on the association between EHRs and postoperative infections, and no significant EHR effects on postoperative infections.

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Chapter 1:

Introduction

1.1. Background

Improving quality of healthcare while controlling costs arising from a complex and fragmented healthcare system continues to be a national priority with many challenges in the United States. To achieve high-quality care while reducing cost, system-wide solutions are required to transform a complex and fragmented health care system into an integrated and coordinated delivery system. One of the system-wide solutions, health information technology (HIT), including electronic health records (EHRs), has the potential to improve healthcare quality and outcomes by innovating healthcare delivery processes such as (1) providing clinicians timely and appropriate patient information, (2) enhancing care coordination, (3) increasing physician compliance to care guidelines, (4) facilitating clinical monitoring from large-scale screening and aggregation of data, (5) improving clinical workflow, (6) improving communication between clinicians and patients as well as among clinicians, and (7) decreasing medication (Appari, Johnson, and Anthony 2013; Bates and Gawande 2003; Chaudhry et al. 2006; Hillestad et al. 2005; Quinn et al. 2012).

Despite these potential benefits, the overall rate of EHR adoption has been slow in the U.S. By 2008, only 11% of hospitals and 13% of physicians had adopted basic EHR systems (DesRoches et al. 2008; Jha et al. 2009). There are significant barriers to adopting an EHR system including high acquisition and implementation costs, lack of technical compatibility between various EHR components, insufficient IT infrastructure, privacy and security concerns, and clinician resistance (Hersh 2004; Hillestad et al. 2005; Jha et al. 2009; Simon, Rundall, and Shortell 2005).

Financial burden is one of the most critical barriers to adopting EHRs (Hersh 2004; Hillestad et al. 2005; Jha et al. 2009; Simon, Rundall, and Shortell 2005). To align the incentives for adoption, the 2009 Health Information Technology for Economics and Clinical Health (HITECH) Act established the Medicare and Medicaid EHR incentive program. In 2011, the Center for Medicare and Medicaid Services (CMS) implemented the incentive program. Under this program up to $30 billion is available for financial incentives to promote "meaningful use" of EHR over 10 years. The Patient Protection and Affordable Care Act (ACA) recognizes the use of health information technology (HIT) as a critical component in achieving its ambitious goal of improving quality while controlling costs.

The EHR incentive program has increased EHR adoption by hospitals and physicians. As of January 2014, hospitals received $13.8 billion, and office-based physicians and clinicians received $6.8 billion in incentives. Between 2008 and 2012, the EHR adoption rate among general acute hospitals increased from 11% to 44% (Hsiao and Hing 2012). During the same period, EHR adoption among office-based physicians increased from 13% to 38% (DesRoches et al. 2008; DesRoches et al. 2013; Hsiao et al. 2013; Jha et al. 2009).

Despite increased EHR adoption by hospitals and physicians under the EHR incentive program as well as the enormous potential of EHRs to improve quality and save costs, doubts about EHR benefits remain. A recent *Wall Street journal* editorial argued that U.S. will spend $1 trillion on HIT without substantial cost savings (Soumerai and Koppel 2012). In addition, two recent nationwide physician surveys indicated that more than half of physicians do not think EHRs that the benefits of EHRs outweigh the costs, and only one third of physicians reported that EHRs improve quality of care (Athenahealth 2013; The Physicians Foundation 2012). Furthermore, the most recent evidence suggests little increased value to Medicare (McCullough, Parente, and Town 2013).

There have been other empirical studies of EHR impact on healthcare use and quality which have mixed findings (Bassi and Lau 2013; Buntin et al. 2011; Chaudhry et al. 2006; Goldzweig et al. 2009; O'Reilly et al. 2012; Poissant et al. 2005). The analytic approach of many of these studies may explain the mixed evidence. First, most of the prior studies did not examine complex EHR functionalities and their mechanisms to improve quality and efficiency, rather they simply use a dichotomous indicator of EHR use. Heterogeneous EHR systems, healthcare settings, and patient profiles are important considerations when examining the impact of IT on healthcare delivery performance, but is not well addressed in prior studies. In addition, barriers to adoption and effective use of EHRs may affect the impact of EHRs on healthcare quality and outcomes. Lastly, most of the prior studies failed to address unobserved confounding related to EHR adoption.

This dissertation addresses 5 major gaps in literature: 1) effectiveness of specific EHR functionalities and their mechanisms, 2) EHR systems, healthcare settings, and patient profiles, 3) barriers to EHR use, 4) valid specification of the quality of care and outcomes measures, and 5) unobserved confounding related to EHR adoption.

1.2. Definitions

1.2.1. Electronic Health Record

"The Electronic Health Record (EHR) is an electronic record regarding patient health information which includes patient demographics, progress note, problems, medications, vital signs, past medical history, immunizations, and laboratory data, and radiology reports." (HealthCare Information and Management Systems Society)

1.2.2. Inter-operability and Intra-operability of Health Information System

Inter-operability is the ability of different health information systems across hospitals to communicate and exchange data while intra-operability is the ability of various health information system components within a hospital to interface with each other.

1.2.3. Health Information Technology for Economic and Clinical Health Act

"The Health Information Technology for Economic and Clinical Health (HITECH) Act, enacted as part of the American Recovery and Reinvestment Act of 2009, was signed into law on February 17, 2009, to promote the adoption and meaningful use of health information technology." (HITECH Act enforcement interim final rule)

1.2.4. Patient Safety

"Patient safety is the absence of the potential for, or occurrence of, healthcare-associated injury to patients created by avoiding medical errors as well as taking action to prevent errors from causing injury" (Agency for Healthcare Research and Quality 2003)

1.3. Key Functionalities of an EHR System

The Institute of Medicine (IOM) outlined 8 key functionalities of an electronic health record system (Tang 2003). These eight functionalities include 1) Health information and data, 2) Decision support, 3) Order entry and support, 4) Results Management, 5) Electronic communication and connectivity, 6) Patient support, 7) Administrative process, and 8) Reporting and population health management. Table 1-1 lists 8 key functionalities with associated EHR components.

Each of 8 key functionalities of the EHR system has been shown to potentially improve healthcare outcomes. First, health information and data provides clinicians with timely access to appropriate patient information for clinical decision-making (Payne et al. 2013; Tang 2003). Decision support has been shown to enhance adherence to clinical guidelines and protocols (Chaudhry et al. 2006; Tang 2003). Order entry and support may improve efficiency of care and clinical workflow as well as administrative efficiency by reducing documentation time and/or electronic claim submission time (Chaudhry et al. 2006; Poissant et al. 2005; Quinn et al. 2012). Results management capabilities can improve efficiency and ensure timely follow-up (Poon et al. 2003; Tang

2003). Electronic communication and connectivity may improve patient safety, quality of care, and public health surveillance (Tang 2003; Wagner et al. 2001). Patient support helps demonstrated significant effectiveness in improving management of chronic conditions, and administrative process such as electronic billing increase administrative efficiency (Tang 2003). Finally, electronic reporting and population health management reduces costs and increase the accuracy of reporting patient safety and quality data, public health data, and disease registries (Tang 2003).

Table 1-1: Key EHR Functionalities and Associated EHR Components

Key EHR Functionalities*	***EHR components associated with key EHR functionalities***
Health information and data	Demographic information Clinical notes Patient problem lists
Decision support	Reminders for guideline-based interventions and/or screening tests Drug-drug interaction alerts Drug-lab interaction alerts
Order entry and support	Computerized orders for prescription Computerized orders for laboratory tests Computerized orders for radiology
Result management	Viewing imaging results Viewing laboratory results
Electronic communication and connectivity	Electronic health information exchange
Patient support	Access to personal health records (PHR) Electronic communication with clinicians
Administrative process	Electronic scheduling/billing
Reporting and population health management	Immunization registries Quality reporting

Note:
* EHR functions defined as key functionalities by the Institute of Medicine (IOM)

1.4. Conceptual Framework

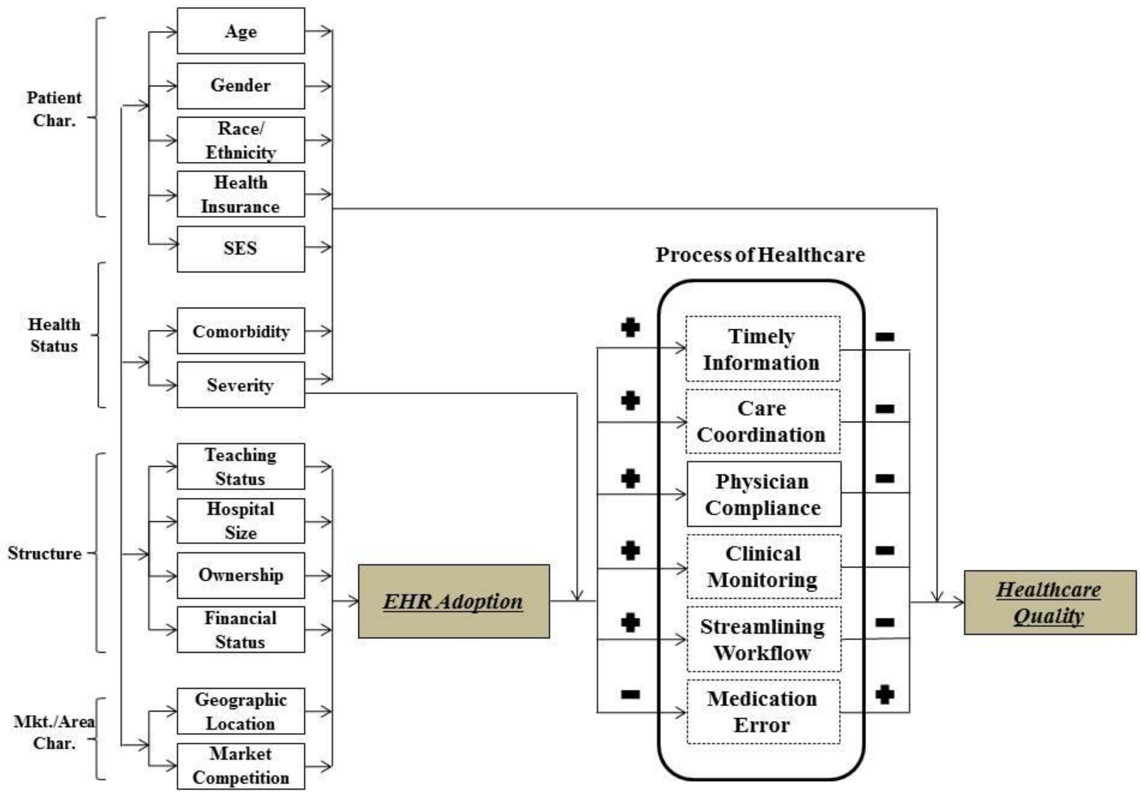
This dissertation combines a modified version of the Donabedian model (Donabedian 1980) and an EHR adoption model (Abdolrasulnia et al. 2008; Bramble et al. 2010; Kazley and Ozcan 2007; Simon, Rundall, and Shortell 2005, 2007) to evaluate the impact of EHR on use of health services and quality of healthcare.

The Donabedian Model of Quality Care consists of system/provider characteristics (structure), the process of medical care, and healthcare quality. The elements of structure include the healthcare system's characteristics (i.e. organization, personnel, specialty mix, financial incentives, patient volume, and access) and provider characteristics (i.e. specialty, financial incentive, belief, and preferences). The process of medical care includes any medical services or products that patients receive and is influenced by a provider's technical and interpersonal style. This framework also lays out an EHR adoption model which indicates that organizational and market/system characteristics are two principal factors which may affect adoption of EHRs (Kazley and Ozcan 2007; Simon, Rundall, and Shortell 2005, 2007).

In addition to elements from the Donabedian model of healthcare quality and the EHR adoption model, this dissertation also includes patient characteristics and health status in its analytic framework. Not only do patient characteristics and health status affect health services use and quality, these two components, which are correlated each other, also correlate with organizational characteristics, market/system characteristics, and EHR adoption.

EHR adoption influences quality of care mostly through the process of healthcare delivery. According to previous studies investigating the mechanisms through which EHRs affect healthcare quality, the use of EHRs can improve quality of care by (1) providing clinicians timely and appropriate patient information, (2) enhancing care coordination, (3) increasing physician compliance to guidelines or a protocol for care, (4) facilitating clinical monitoring through large-scale screening and aggregation of data, (5) improving clinical workflow, (6) improving communication between clinicians and patients as well as among clinicians, and (7) decreasing medication errors and improving medication dosing (Appari, Johnson, and Anthony 2013; Bates and Gawande 2003; Chaudhry et al. 2006; Hillestad et al. 2005; Quinn et al. 2012). Figure 1 is a representation of a conceptual model for the effect of EHRs on healthcare quality.

Figure 1-1: Conceptual Model (The Effect of EHRs on Healthcare Quality)



1.5. Aim and Scope

The main objective of this dissertation is to examine the impact of EHR use on health services utilization and quality of healthcare both in ambulatory and hospital care settings. Each of the three essays employs regression analysis using large patient administrative data to provide results that have external validity.

The first essay examines the impact of core EHR functionalities on preventive health behavior counseling services provided at primary care visits using nationally representative data. I hypothesize that core EHR functionalities, either individually or in combination, would increase the likelihood that preventive health behavior counseling services are provided at a primary care visit.

The second essay examines whether common barriers to the implementation and effective usage of EHRs including (1) intra-operability as measured by the number of vendor products and (2) staff support as measured by physician resistance influence the impact of EHRs on healthcare quality as measured by hospital-acquired adverse patient safety events. I hypothesize that intra-operability of an EHR system moderates EHR effects on hospital-acquired adverse patient safety events, and physician resistance mediates the effects.

The third essay examines whether EHR use (1) improves process of care as measured by compliance to infection-prevention guidelines for surgical patients and (2) reduces postoperative infections. I also hypothesize that compliance to infection-prevention guidelines for surgical patients mediates the impact of EHRs on postoperative infections.

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Chapter 2:

Impact of Electronic Health Records on Delivery of Health Behavior Counseling Services:

The Role of Complementary Functionalities

2.1. Background

Unhealthy behaviors and chronic diseases are key drivers of healthcare expenditures as well as premature mortality and morbidity in the United States (Anderson 2010; Cohen et al. 2011). In 2009, 145 million Americans had at least one chronic condition, and 84% of healthcare expenditures were associated with this population (Anderson 2010). A growing body of evidence shows that a reduction in unhealthy behaviors can prevent the onset of chronic diseases, help patients manage their conditions effectively, and slow disease progression (Aldana et al. 2003; Hu et al. 2001; Knoops et al. 2004; Speck et al. 2010; Stampfer et al. 2000; Williamson et al. 2000). It is estimated that 40 million Americans have chronic illnesses that could be prevented or delayed by modest reductions in unhealthy behaviors (DeVol et al. 2007).

Disease prevention and management is a major emphasis of the Patient Protection and Affordable Care Act (ACA) which aims to improve quality while reducing costs. The ACA mandates that new private health insurance plans cover 45 preventive health services including tobacco, alcohol, and diet counseling (Cassidy 2010; Koh and Sebelius 2010). The ACA also expands Medicare coverage for annual wellness visits (Cassidy 2010). Health education/counseling in primary care has been shown to improve early detection, prevention, and management of chronic conditions by helping patients identify risk factors and adopt healthy behaviors (Elder, Ayala, and Harris 1999; Whitlock et al. 2002).

Two challenges in providing health education/counseling in the outpatient setting are physician time constraints and ability to tailor the education to each patient in the panel. Health information technology (HIT) can potentially reduce these barriers by improving the patient information that is available at the time of care. EHRs may provide physicians with patient-specific counseling information and clinical decision support. EHR systems may also improve efficiency of care by enhancing clinical workflow, which allows physicians to spend longer periods of time with patients and to provide more health behavior counseling services (Chaudhry et al. 2006; Poissant et al. 2005; Clancy and Slutsky 2007).

The ACA legislation also recognizes the use of health information technology (HIT) as part of the solution to achieving its ambitious goal of improving quality while controlling costs. Prior to the ACA, the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act established the Medicare and Medicaid EHR incentive program to encourage physicians to adopt the meaningful use of EHRs. If physicians adopt EHRs and satisfy the program requirements, they can receive up to $44,000 over 5 years through Medicare or $63,750 over 6 years through Medicaid (Blumenthal and Tavenner 2010). The EHR incentive program has helped increase the EHR adoption by physicians. As of January 2014, office based physicians and clinicians received 6.8 billion dollars in incentives. Between 2005 and 2011, the EHR adoption rate among office based physicians increased from 23.9% to 57.0% (Hsiao and Hing 2012). The rate of increase in EHR adoption during the same period is even higher among family physicians (24.8% to 66.4%) (Xierali et al. 2013).

In this article, we estimated the impact of key EHR functionalities on preventive health behavior counseling services provided at primary care visits using nationally representative data. We hypothesized that these EHR functionalities, either individually or in combination, would increase the likelihood that preventive health behavior counseling services are provided at a primary care visit.

2.2. Conceptual Framework

The Institute of Medicine (IOM) outlined eight key functionalities of an EHR system (Table 2-1) (Tang 2003). The Expert Consensus Panel (ECP) to the HIT adoption initiative of the Office of the National Coordinator for Health Information Technology (ONC) selected four of the eight functionalities identified by the IOM as core functionalities of an EHR: 1) health information and data, 2) decision support, 3) order entry and support, and 4) results management (Blumenthal et al. 2006).

Each of the four core functionalities of the EHR system has been shown to potentially impact health behavior counseling services either directly or indirectly and improve health outcomes. First, health information and data provides physicians with timely access to appropriate patient information for clinical decision-making such as providing appropriate health behavior counseling (Payne et al. 2013; Tang 2003). Decision support has been shown to enhance adherence to clinical guidelines and protocols (Chaudhry et al. 2006; Tang 2003) through automated reminders. For example, EHRs may promote the delivery of health behavior counseling during primary care visits by supporting automated reminders and counseling protocols. Order entry and support may improve efficiency of care and clinical workflow as well as administrative efficiency by reducing documentation time and/or electronic claim submission time

(Chaudhry et al. 2006; Poissant et al. 2005; Quinn et al. 2012). This increase in efficiency may allow physicians to spend more time on direct patient care including health behavior counseling services. Lastly, results management capabilities can improve efficiency and ensure timely follow-up including relevant health behavior counseling services by facilitating the interpretation of test results and notifying the provider of abnormal results (Poon et al. 2003; Tang 2003).

In addition to the potential impact of a specific EHR function alone, the use of multiple functionalities may also influence the delivery of health behavior counseling services as complements. Specifically, one function may be a complementary input to another function impacting on the provision of health behavior counseling. For example, decision support can be a complementary function to health information and data, since health information and data, together with decision support, may enhance health behavior counseling services. Reminders to provide counseling without complementary health information and data may be of little use to the clinician and therefore not impact the provision of health behavior counseling.

Consequently, we might hypothesize that EHR functionalities, either individually or in combination, would increase health behavior counseling in primary care by providing adequate patient health information with clinical decision support and improving efficiency and workflow.

2.3. Literature Review

Despite these potential benefits from adopting EHRs and health behavior counseling services, only a handful of studies investigated the impact of EHRs on health behavior counseling services, and their findings are limited. Recently, several state-wide and national studies have investigated the impact of EHRs on health behavior counseling in ambulatory care (Furukawa 2011; Garrido et al. 2005; Linder et al. 2007; Romano and Stafford 2011). In general, the results from these studies have shown that the impact of EHRs on promoting health behavior counseling services is minimal.

Garrido et al. (2005) compared ambulatory care visits before and after the implementation of EHR system in Colorado and Northwest regions of Kaiser Permanente health system. They examined the effect of comprehensive EHR systems on quality of ambulatory care visits including smoking cessation counseling and found that the frequency of advice on smoking cessation in office visits increased after the EHR system implementation.

Linder et al. (2007) evaluated the effect of EHR use on 17 ambulatory quality indicators including three types of preventive behavior counseling services (smoking cessation counseling, diet counseling, and exercise counseling to adolescents) using the 2003-2004 National Ambulatory Medical Care Survey (NAMCS). Their cross-sectional analysis found no significant association between EHR use and preventive behavior counseling services.

Romano and Stafford (2011) also examined the association between EHR use and frequency of five types of preventive behavior counseling services in the ambulatory care setting using the 2005-2007 NAMCS data. Of all 5 preventive behavior counseling services, EHR use was significantly and positively associated with only one counseling service (diet counseling). Although this study found some association between EHR use and frequency of health behavior counseling, these findings were limited to the only one type of preventive behavior counseling. In addition, they did not control for the endogeneity between EHR adoption and health behavior counseling delivery due to unobservable physician characteristics.

Finally, Furukawa (2011) analyzed the 2006-2007 NAMCS data to evaluate the association between EHR use and a composite measure of 9 health behavior counseling services. He demonstrated positive and significant association between EHR use and probability of any health behavior counseling. Although this study found significant association between EHR use and overall health behavior counseling services, the study did not address the endogenous adoption of EHRs by physicians. In addition, this study used overall adoption of EHR instead of specific EHR elements that potentially promote health behavior counseling services. This latter point is important. National policy dictates a meaningful use standard, so understanding what components of EHR are effective is important to refine the definition of 'meaningful use'.

In summary, while there have been several important studies on EHR, there appear to be three major limitations in EHR literature on health behavior counseling services. First, most of the prior studies examined the impact of a specific EHR component (e.g. CPOE, Decision support) or overall adoption level of EHR system (e.g. Basic/Comprehensive EHR use) not distinguishing between functionality of the EHR adopted. Second, findings from earlier works were limited to only a few types of health behavior counseling services. Third, most earlier studies did not address the problems of endogenous adoption of EHR.

In this article, we address these limitations using direct measures for eight EHR components potentially promoting health behavior counseling services and a composite measure for health behavior counseling services. We examine the impact of specific elements of the EHR system on health behavior counseling services. Moreover, we also examine whether one EHR element plays the role of a supplement or is a necessity for other elements, and whether a computerized notification system for abnormal test results addresses information overload in result management. Finally, we address the endogenous adoption of EHR by employing propensity score matching methods.

2.4. Methods

2.4.1. Data

The study used the 2007-2010 National Ambulatory Medical Care Survey (NAMCS). The NAMCS is a national probability sample survey administrated by the National Center for Health Statistics for the Centers for Disease Control and Prevention. The NAMCS collects data on patient visits to non-federally employed office-based physicians in the United States. This dataset, described in detail in Hsiao et al (2010), has been used in previous research assessing the impact of EHR on health behavior counseling (Furukawa 2011; Hsiao et al. 2013; Linder et al. 2007; Romano and Stafford 2011). Because we were interested in examining the influence of the EHR on the provision of health behavior counseling in the primary care setting, we only included patient visits to primary care physicians (general practitioners, family practitioners, or general internists) by patients 18 years of age or older. We examined 34,315 adult patient visits to 1,425 primary care physicians during 2007-2010.

2.4.2. Health Behavior Counseling Services

The NAMCS contains data on the ordering or provision of health behavior counseling and education during patient encounters. In this study, we examine a composite measure of health behavior counseling services obtained from the NAMCS, which includes education on asthma, diet/nutrition, exercise, growth/development, injury prevention, stress management, tobacco use/exposure, and weight reduction.

2.4.3. EHR Adoption

The key independent variables in this study are eight measures for the adoption of EHR components pertaining to the four core functionalities of an EHR system as defined by the IOM and ONC. In the NAMCS survey, physicians reported on which components their EHRs included as well as whether their practices used full or partial EHR systems. We examined eight EHR components relating to the four core EHR functionalities: clinical notes, patient problem lists, electronic reminders (e-Reminders) for guideline-based interventions/screening tests, computerized orders for prescriptions, computerized orders for laboratory tests, imaging results viewer, laboratory results viewer, and highlighting of laboratory results that are out of range.

2.4.4 Statistical Models

We used multivariable regression models based on a linear probability model to assess the association between EHR core components and health behavior counseling services provided during primary care visits. The basic specification is of the following form:

$$\text{Health Counseling}_{ij} = \alpha + \beta_1 \text{EHR Component}_j + \beta_2 D_j + \beta_3 P_{ij} + \varepsilon_{ij}$$

Where **Health Counseling** is an indicator equal to one if any health counseling services are provided during visit i to physician j. **EHR Component** is a vector of the adoption of EHR components including 1) eight EHR components pertaining to four core functionalities of an EHR system and 2) two interaction terms between e-Reminders and EHR components relating to the health information and data functionality. These two interaction terms (clinical notes*e-Reminders & patient problem lists*e-Reminders) reflect complementary effect between the health information and data functionality and the decision support functionality. **D** is a vector of physician characteristics, and **P** is a vector of patient characteristics, health status of patients, and visit characteristics.

We chose the linear probability model because we used interactions between the key EHR elements to assess complementarities between technologies, and interaction terms are complex to interpret in nonlinear models, including logistic regression (Ai and Norton 2003; Karaca-Mandic, Norton, and Dowd 2011). We estimated robust (Huber-White) standard errors to address the heteroskedasticity in the linear probability model. We controlled for a variety of potential confounders, including patient demographic characteristics, health status (reason for visit, chronic conditions), visit characteristics (own MD, weekend, new patient), physician characteristics (specialty, practice ownership, predominant payer model) and other covariates such as geographic region, metropolitan statistical area (MSA) status, and survey year. In addition, as a robustness check, we also estimated all equations using a logit model, and the results for all the major variables were similar to those from the linear probability model.

2.4.5. Confounding of EHR Adoption and Health Behavior Counseling Services

EHR adoption and health behavior counseling services are potentially correlated with unobservable characteristics of patients (e.g. severity or socioeconomic status) or physicians (e.g. physician age). This would lead to a spurious correlation between EHR use and health behavior counseling services. To address this issue, we created weights via propensity score matching and re-weighted our data. As a robustness check, we also included the propensity score weight as a covariate in the regression.

Using the propensity score matching routine in Stata 12 (StataCorp LP, College Station, Texas), we created each visit's propensity scores with a logit regression of having basic EHRs, controlling for physician, patient, and visit characteristics. Visit weights were then constructed by the inverse of the propensity score for treated visits, and the inverse of one minus the propensity score for control visits. We constructed two different propensity score weights using two pairs of treated visits and control visits. The first pair consists of "visits with full EHR systems" and "visits with no or partial EHR systems" while the second pair comprises "visits with partial or full EHR systems" and "visits with no EHR systems." We restricted the analysis to visits within a common region of support (Becker and Ichino 2002). To gauge the stability of our models and any potential differences in important coefficients, we estimated both a standard model without propensity score matching and a reweighted model using propensity scores to demonstrate any effects of failing to deal with unobserved confounding. To assess the robustness of our findings, we also ran regressions including propensity score weights as a covariate.

2.5. Results

2.5.1. Descriptive Statistics

In the raw sample, adoption rates for the eight EHR components were >40% except for e-Reminders for intervention/screening tests (39.2 %). The laboratory results viewer (60.0 %), computerized order for prescriptions (47.3 %), and clinical notes (46.4 %) were the most frequently used EHR components. The adoption rate of patient problem lists, computerized order entry for laboratory tests, imaging results viewer, and highlighting of out-of-range lab results ranged from 41.8 to 48.0%. The overall rate of at least one health behavior counseling service provided was approximately 40 % in both the raw and weighted samples.

Table 2-2 contains descriptive statistics for the sample as well as health behavior counseling service rates and EHR use. Column 1 shows summary statistics from the raw (unweighted) sample. Column 2 presents summary statistics from the propensity score weighted sample using "visits with full EHR systems" as treated visits and "visits with no or partial EHR systems" as control visits. Column 3 shows the weighted sample of "visits with partial or full EHR systems" as treated visits and "visits with no EHR systems" as control visits.

2.5.2. Propensity Score Matching

Propensity score weights from both pairs of treated and control visits (weighted sample (1) & weighted sample (2) in table 2-2) substantially reduce the endogeneity bias. In the weighted sample (1), the average absolute value of the bias in the 59 physician, patient, and visit characteristics, including all of the covariates except for dependent/independent variables in table 2-2, between "visits with full EHR systems" and "visits with no or partial EHR systems" was reduced from 6.6 to 1.7 due to the propensity score matching. While 46 of 59 physician, patient, and visits characteristics in the raw data predicted "visits with full EHR systems" (within a 95% level of statistical significance), only 11 physician, patient, and visits characteristics still predict "visits with full EHR systems" after matching.

In the weighted sample (2) the average absolute value of the bias in the 59 physician, patient, and visit characteristics between "visits with partial or full EHR systems" and "visits with no EHR systems" was reduced from 6.3 to 1.7 due to the propensity score matching. While 39 of 59 physician, patient, and visits characteristics in the raw data predicted "visits with partial or full EHR systems" in patient visits (within a 95% level of statistical significance), only 16 physician, patient, and visits characteristics still predict "visits with partial or full EHR systems" after matching.

2.5.3. Adjusted EHR Impact on Health Behavior Counseling Services

Results of the multivariable model are in Table 2-3. We estimated a standard model without propensity score matching (Model 1), two reweighted model (Models 2 and 4), and two alternative propensity score matching models including the propensity score weight as a covariate (Models 3 and 5). Overall, estimates from the five models were similar.

Four of the EHR components (clinical notes, computerized order entry of prescriptions, computerized order entry of labs, and highlighting of abnormal lab results) were individually associated with more frequent provision of health behavior counseling services. The e-reminder, image viewer, and lab viewer components, on the other hand, were associated with significant decreases in the rate of health behavior counseling services. Patient problem lists had no statistically significant impact on health behavior counseling service rates.

Even though patient problem lists and e-Reminders were not individually associated with increases in the delivery of health behavior counseling services, the combination of both components was associated with a significant increase in the probability of health behavior counseling being provided. Similarly, while the lab viewer was individually associated with a significant decrease in the probability of health behavior counseling service being provided, the combination of the lab viewer with highlighting of abnormal lab results was associated with a significant increase in the probability of a health behavior counseling service being provided. These findings indicate two complementary effects between patient problem lists and reminders for guideline-based interventions/screening tests and lab viewer and highlighting of abnormal lab results.

Table 2-4 reports marginal impacts and cumulative impacts of different levels of EHR functionalities using linear combinations of coefficients for each component and interactions estimated from Table 2-3. We started with health information and data, the most basic EHR function, and added more advanced functions/components in this order: order entry and support, result management without notification system, decision support, and notification system for abnormal test results. The two EHR functions that had the greatest marginal impact on the probability of health behavior counseling service being delivered were health information and data (2.3% to 6.1%) and order entry and support (3.2% to 5.4%). Although laboratory results management without a notification system has a negative marginal impact (-4.5% to -2.3%), having a notification system for abnormal test results has positive marginal impacts (2.7% to 3.8%), indicating that computerized notification of relevant critical information may help physicians better identify problem areas and initiate counseling.

Availability of all eight EHR components was associated with a 6.1-7.9% increase in the probability of health behavior counseling services being provided ($P < .01$) and a relative impact of 15.3-19.5%. Defining the optimal combination of EHR components as those components associated either individually or in combination with higher rates of health behavior counseling services delivered , we found that 7 of the EHR components (excluding imaging results) increased the probability of health behavior counseling services being delivered by 9.5-10.9 % ($P < .01$) and had a relative impact of 24.0- 26.9%.

2.5.4. Sensitivity Analyses

The results from multivariable regression models cannot identify whether EHRs simply enhance documenting health behavior counseling services or actually helps to provide more counseling services. To ensure our results were not entirely driven by increasing documentation of counseling services, we performed sensitivity analyses to estimate the effect of core EHR functionalities on new prescription of Bupropion at visits by current smokers. A new Bupropion prescription may be an appropriate proxy for actual smoking cessation counseling because Bupropion is commonly used as a smoking cessation medication. We found that the combination of patient problem list and e-Reminder was associated with a significant increase in the probability of new prescription of Bupropion at visits by current smokers (Table 2-5).

2.6. Discussion

We investigated the impact of eight EHR components that mapped to the IOM and ONC defined four core EHR functionalities on the frequency of health behavior counseling provided during primary care visits. Two functionalities, order entry and health information and data, were independently associated with increases in the probability of health behavior counseling service delivery. Two functionalities, decision support and results management, were associated with decreases in the provision of health behavior counseling services when these components were used alone. These negative associations may indicate that physicians who have decision support functions without adequate complementary patient health information are less likely to recognize opportunities for counseling. In addition, physicians with a results management function but without a notification system for abnormal results may have experienced information overload.

Reminders for guideline-based interventions and/or screening tests were associated with more health behavior counseling services when combined with patient problem lists. This implies that decision support and health information play complementary roles. The laboratory results viewer was also associated with more health behavior counseling services when it was implemented with a computerized notification system for abnormal results, implying that this feature improved the management process.

Our findings confirm other studies that have found computerized notification of relevant critical information, such as the highlighting of abnormal test results, to be an important complementary technology within an EHR system (Singh et al. 2009; Singh et al. 2010). Our findings also suggest that there are also potential unintended consequences of HIT and EHR systems, which can negatively impact quality, efficiency, and safety of care (Ash, Berg, and Coiera 2004; Harrison, Koppel, and Bar-Lev 2007; Zhan et al. 2006). EHRs can result in information overload to the clinician, obstructing timely and appropriate assessment of test results and delivery of follow-up services such as health behavior counseling (Murphy et al. 2012). Primary care physicians are especially vulnerable to information overload as they have to review and manage many imaging and test results (Poon et al. 2003; Poon et al. 2004). A recent survey of physicians found that even though the Medicare and Medicaid EHR incentive programs have substantially increased EHR adoption by physicians, clinicians have become more dissatisfied with their EHRs' ability to decrease workload

(34% “very dissatisfied” in 2012 vs. “18%” very dissatisfied in 2010) in part due to the influx of irrelevant information provided by EHR systems (American EHR Partner 2013).

The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act established the Medicare and Medicaid EHR incentive program to encourage physicians to adopt the meaningful use of EHRs. The EHR incentive program has helped increase EHR adoption by physicians with about 20% of physicians in the U.S. receiving an incentive payment in May 2012 (Centers for Medicare and Medicaid Services 2012). Between 2005 and 2011, the EHR adoption rate among office based physicians increased from 23.9% to 57.0% with even larger growth rates among family physicians (24.8% -66.4%) (Hsiao and Hing 2012; Xierali et al. 2013).

The stage 2 meaningful use criteria for the CMS EHR incentive program covers the four core EHR functionalities that we examined in this study but some of the functionalities are not mandatory (Federal Register 2012). Specifically, the stage 2 meaningful use criteria include the goal to “incorporate clinical lab-test results into EHR as structured data” as one of the core objectives, which covers “computerized notification system for abnormal lab results.” One of the menu objectives, which can be chosen electively by physicians, is “imaging results consisting of the image itself and any explanation or other accompanying information” covers computerized notification of relevant critical information on imaging results.

Our results suggest that CMS should include all four functionalities as mandatory core objectives for the EHR incentive program. We found that a combination of EHR components covering all four core EHR functionalities was associated with a 24.0-26.9% increase in the delivery of health behavior counseling services.

This study has several limitations. First, the NAMCS cannot identify whether EHRs simply enhance documenting health behavior counseling services or actually helps to provide more counseling services. However, findings from the sensitivity analyses suggest that EHRs actually increase health behavior counseling, not just enhancing documentation of counseling services. Second, information on the diversity and complexity of EHR systems and functionalities used in clinical practices in the NAMCS data was limited. Thus, this study did not capture the effects of unobserved features of EHR systems such as types of vendors, data architecture, and end-user interface. Third, the NAMCS did not include sufficient information on both patient and physician characteristics, and these unobservable characteristics such as socioeconomic status of patients and physician age confounded estimates of the relationship between EHR adoption and delivery of health behavior counseling services. However, the propensity score matching method allows us to examine whether unobserved factors confound estimates of the relationship between EHR adoption and delivery of health behavior counseling services. The estimates in our standard model without propensity score matching (Model 1) are similar to those in our propensity score models (Model 2-4).

The CMS EHR incentive program requires hospitals and physician practices to meet the meaningful use criteria of EHRs. The very concept of 'meaningful use' emphasizes the importance of EHR benefits in motivating the policy. This study provides empirical evidence that the appropriate design of an EHR system including core EHR functionalities with complementary components is essential to achieve the EHR benefits of improving primary clinical care.

2.7. Conclusion

EHR systems with certain functionalities have the potential to enhance early detection, prevention, and management of disease by promoting the provision of appropriate health behavior counseling services in primary care. Meaningful use criteria should be evaluated to assure they encourage the adoption of EHR systems with core functionalities shown to improve clinical care.

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Table 2-1: Core EHR Functionalities and Associated EHR Components

Core EHR Functions as defined by IOM and ONC [a]	***EHR components included in NAMCS***
Health information and data	Clinical notes Patient problem lists
Decision support	Reminders for guideline-based interventions and/or screening tests (e-reminder)
Order entry and support	Computerized orders for prescriptions Computerized orders for laboratory tests
Result management	Imaging results viewer Laboratory results viewer Highlighting of out-of-range lab results

Note:
[a] EHR functions defined as key functionalities by the Institute of Medicine (IOM) and selected as core functionalities by the Expert Consensus Panel (ECP) to the HIT adoption initiative of the Office of the National Coordinator for Health Information Technology (ONC).

Table 2-2: Descriptive Statistics

Variables	***Raw Sample***	***Weighted Sample (1)[a,b]*** *Full EHR vs. No/partial EHR*	***Weighted Sample (2)[a,c]*** *Partial/full EHR vs. No EHR*
Dependent/key independent variables			
Health behavior counseling service rate	0.400	0.405	0.397
EMR use:			
Clinical notes	0.464	0.586	0.460
Patient problem list	0.418	0.506	0.413
e-Reminder	0.392	0.470	0.384
Clinical notes · e-Reminder	0.334	0.428	0.324
Patient problem list · e-Reminder	0.281	0.358	0.272
Computerized order for prescriptions	0.473	0.578	0.471
Computerized order for laboratory tests	0.441	0.514	0.425
Imaging results viewer	0.446	0.489	0.439
Laboratory results viewer	0.600	0.665	0.590
Highlighting of out-of-range lab values	0.480	0.526	0.468
Patient's characteristics			
Mean age (SD)	52.11 (17.96)	52.00 (18.02)	52.20 (17.98)
Female	0.597	0.595	0.596
Race/ethnicity:			
White, Non-Hispanic	0.655	0.657	0.657
Black, Non-Hispanic	0.136	0.136	0.135
Hispanic	0.102	0.099	0.101
Other race, Non-Hispanic	0.108	0.108	0.107
Primary source of payment:			
Private insurance	0.437	0.440	0.439
Medicare	0.237	0.236	0.239

Medicaid	0.135	0.132	0.133
Other	0.191	0.193	0.189
Low-income area	0.311	0.305	0.309
Higher education area	0.220	0.224	0.221
Patient's health status			
Major reason for visit:			
New problem	0.390	0.390	0.387
Chronic problem (routine)	0.320	0.325	0.326
Chronic problem (flare up)	0.078	0.079	0.078
Pre/Post surgery	0.014	0.013	0.014
Preventive care	0.176	0.171	0.173
Other reason for visit	0.022	0.022	0.022
Related to injury	0.099	0.099	0.097
Chronic conditions:			
Number of chronic conditions (SD)	1.52 (1.46)	1.52 (1.46)	1.52 (1.46)
Arthritis	0.146	0.146	0.146
Asthma	0.067	0.064	0.065
Cancer	0.037	0.038	0.037
Cerebrovascular disease	0.019	0.019	0.018
Chronic renal failure	0.015	0.015	0.016
Congestive heart failure	0.022	0.023	0.022
Chronic obstructive pulmonary disease	0.061	0.062	0.062
Depression	0.139	0.137	0.137
Diabetes	0.176	0.176	0.176
Hyperlipidemia	0.263	0.264	0.263
Hypertension	0.383	0.381	0.382
Ischemic heart disease	0.040	0.040	0.041
Obesity	0.119	0.117	0.117
Osteoporosis	0.037	0.036	0.038
Visit's characteristics			
Visit to own primary care physician	0.808	0.810	0.811

Referred visit	0.025	0.025	0.024
New patient	0.099	0.101	0.098
Number of visits in last 12 months:			
No visit in last 12 months	0.145	0.145	0.143
1 visit in last 12 months	0.143	0.141	0.143
2 visits in last 12 months	0.140	0.139	0.141
3 or more visits in last 12 months	0.571	0.575	0.574
Weekend visits	0.015	0.015	0.015
Seen by other clinicians than MD	0.452	0.436	0.445
Physician characteristics			
Physician specialty:			
General and family practice	0.716	0.719	0.711
Internal medicine	0.284	0.281	0.289
Ownership:			
Physician or physician group	0.558	0.555	0.561
HMO	0.024	0.024	0.022
Community health center	0.272	0.272	0.270
Medical/Academic health center	0.022	0.022	0.021
Other type of ownership	0.125	0.127	0.127
Solo practice	0.255	0.266	0.262
Employment status:			
Owner	0.433	0.440	0.440
Employee	0.520	0.505	0.512
Contractor	0.048	0.055	0.049
Telephone consults	0.504	0.508	0.509
Physician's incentive on counseling services			
Over 50% of revenue from capitation	0.037	0.038	0.039
Over 50% of revenue from managed care contract	0.300	0.290	0.294
Over 50% of revenue from case rate	0.020	0.021	0.021

<u>Other covariates</u>			
Metropolitan Statistical Area (MSA)	0.854	0.866	0.858
Geographic region:			
Northeast	0.174	0.174	0.176
Midwest	0.260	0.258	0.257
South	0.316	0.325	0.327
West	0.250	0.243	0.240
Survey year:			
2007	0.252	0.257	0.257
2008	0.254	0.253	0.258
2009	0.275	0.273	0.273
2010	0.219	0.217	0.212
N	34,315	34,315	34,315

Note: Standard errors are in parentheses.
[a] Weighted samples were created using the propensity score matching method.
[b] Weighted sample (1) used "visits with full EHR systems" as treated visits and "visits with no or partial EHR systems" as control visits.
[c] Weighted sample (2) used "visits with partial or full EHR systems" as treated visits and "visits with no EHR systems" as control visits.

Table 2-3: Estimated Impact of Electronic Health Record Functionality on the Probability of Health Behavior Counseling Service Delivery

Dependent variable: Health behavior counseling services	***Raw Sample***	***Sample with Propensity Score Weights [a]***			
		Full EHR vs. No/partial EHR [b]		*Partial/full EHR vs. No EHR [c]*	
		Weighted Sample [d]	*PS weight as a covariate [e]*	*Weighted Sample [d]*	*PS weight as a covariate [e]*
	(1)	(2)	(3)	(4)	(5)
<u>Key independent variables</u>					
Clinical notes	0.0631***	0.0384***	0.0668***	0.0566***	0.0638***
	(0.0103)	(0.0118)	(0.0104)	(0.0111)	(0.0103)
Patient problem lists	-0.0067	-0.0153	-0.0060	-0.0132	-0.0066
	(0.0093)	(0.0107)	(0.0093)	(0.0100)	(0.0093)
e-Reminder	-0.0386***	-0.0432***	-0.0396***	-0.0405***	-0.0382***
	(0.0115)	(0.0122)	(0.0115)	(0.0123)	(0.0115)
Clinical notes • e-Reminder	-0.0006	0.0129	0.0007	0.0093	-0.0017
	(0.0159)	(0.0177)	(0.0159)	(0.0172)	(0.0159)
Patient problem list • e-Reminder	0.0318**	0.0694***	0.0322**	0.0435***	0.0318**
	(0.0138)	(0.0161)	(0.0137)	(0.0147)	(0.0138)
Computerized order for prescriptions	0.0330***	0.0232**	0.0352***	0.0377***	0.0336***
	(0.0079)	(0.0092)	(0.0080)	(0.0085)	(0.0079)
Computerized order for laboratory tests	0.0138*	0.0082	0.0132*	0.0158**	0.0129*
	(0.0075)	(0.0089)	(0.0075)	(0.0080)	(0.0075)
Imaging results viewer	-0.0379***	-0.0304***	-0.0384***	-0.0299***	-0.0378***
	(0.0067)	(0.0078)	(0.0067)	(0.0072)	(0.0067)
Laboratory results viewer	-0.0238**	-0.0222*	-0.0230**	-0.0447***	-0.0239**
	(0.0098)	(0.0118)	(0.0098)	(0.0105)	(0.0098)

Highlighting of out-of-range lab results	0.0272***	0.0376***	0.0266***	0.0307***	0.0270***
	(0.0086)	(0.0102)	(0.0086)	(0.0091)	(0.0086)
Propensity Score Weight (Full EHR vs. No/partial EHR)			-0.0048**		
			(0.0021)		
Propensity Score Weight (Full/partial EHR vs. No EHR)					-0.0049
					(0.0033)
Patient's characteristics					
Age group: (Ref: Age 18-34)					
Age 35-49	-0.0117	-0.0049	-0.0118	-0.0072	-0.0117
	(0.0079)	(0.0094)	(0.0079)	(0.0085)	(0.0079)
Age 50-64	-0.0344***	-0.0353***	-0.0346***	-0.0341***	-0.0345***
	(0.0083)	(0.0098)	(0.0083)	(0.0089)	(0.0083)
Age 65+	-0.0645***	-0.0726***	-0.0649***	-0.0582***	-0.0645***
	(0.0110)	(0.0128)	(0.0110)	(0.0118)	(0.0110)
Female	-0.0054	-0.0060	-0.0054	-0.0101*	-0.0054
	(0.0054)	(0.0063)	(0.0054)	(0.0058)	(0.0054)
Race/ethnicity: (Ref: White, Non-Hispanic)					
Black, Non-Hispanic	0.0087	-0.0002	0.0086	0.0073	0.0085
	(0.0083)	(0.0100)	(0.0083)	(0.0090)	(0.0083)
Hispanic	0.0359***	0.0371***	0.0357***	0.0264***	0.0359***
	(0.0093)	(0.0107)	(0.0093)	(0.0099)	(0.0093)
Other race, Non-Hispanic	0.0162*	0.0125	0.0162*	0.0046	0.0161*
	(0.0090)	(0.0113)	(0.0090)	(0.0096)	(0.0090)
Primary source of payment: (Ref: Private insurance)					
Medicare	-0.0177*	-0.0213**	-0.0175*	-0.0227**	-0.0177*
	(0.0092)	(0.0107)	(0.0092)	(0.0098)	(0.0092)

Medicaid	0.0013	0.00038	0.0015	0.0035	0.0011
	(0.0091)	(0.0111)	(0.0091)	(0.0098)	(0.0091)
Other	0.0254***	0.0269***	0.0254***	0.0353***	0.0252***
	(0.0079)	(0.0094)	(0.0079)	(0.0085)	(0.0079)
Low-income area	-0.0149**	-0.0201***	-0.0150**	-0.0181***	-0.0150**
	(0.0062)	(0.0073)	(0.0062)	(0.0067)	(0.0062)
Higher education area	0.0197***	0.00228	0.0200***	0.00973	0.0197***
	(0.0066)	(0.0078)	(0.0066)	(0.0071)	(0.0066)
Patient's health status					
Major reason for visit: (Ref: New problem)					
Chronic problem (routine)	0.0835***	0.0923***	0.0837***	0.0837***	0.0837***
	(0.0065)	(0.0078)	(0.0065)	(0.0070)	(0.0065)
Chronic problem (flare up)	0.0555***	0.0630***	0.0556***	0.0604***	0.0557***
	(0.0101)	(0.0120)	(0.0101)	(0.0111)	(0.0101)
Pre/Post surgery	-0.0161	-0.0230	-0.0163	-0.0166	-0.0157
	(0.0217)	(0.0235)	(0.0217)	(0.0236)	(0.0217)
Preventive care	0.0876***	0.0972***	0.0873***	0.0849***	0.0875***
	(0.0076)	(0.0088)	(0.0076)	(0.0081)	(0.0076)
Other reason for visit	0.0034	0.0364*	0.0039	0.0139	0.0037
	(0.0172)	(0.0208)	(0.0173)	(0.0183)	(0.0172)
Related to injury	0.0322***	0.0383***	0.0322***	0.0277***	0.0321***
	(0.0088)	(0.0106)	(0.0088)	(0.0094)	(0.0088)
Chronic conditions:					
1 chronic conditions	0.0712***	0.0685***	0.0710***	0.0695***	0.0712***
	(0.0081)	(0.0097)	(0.0081)	(0.0088)	(0.0081)
2+ chronic conditions	0.0870***	0.0802***	0.0866***	0.0866***	0.0868***
	(0.0131)	(0.0154)	(0.0131)	(0.0140)	(0.0131)
Arthritis	-0.0158*	-0.0123	-0.0157*	-0.0124	-0.0159*
	(0.0081)	(0.0097)	(0.0081)	(0.0087)	(0.0081)
Asthma	0.0148	0.0109	0.0144	0.0165	0.0147

	(0.0111)	(0.0125)	(0.0111)	(0.0118)	(0.0111)
Cancer	0.0031	0.0186	0.0027	0.0038	0.0029
	(0.0140)	(0.0160)	(0.0140)	(0.0151)	(0.0140)
Cerebrovascular disease	0.0116	0.0011	0.0115	0.0076	0.0113
	(0.0196)	(0.0233)	(0.0196)	(0.0211)	(0.0196)
Chronic renal failure	0.0380*	0.0550**	0.0379*	0.0384	0.0384*
	(0.0219)	(0.0268)	(0.0219)	(0.0240)	(0.0219)
Congestive heart failure	-0.0315*	-0.0353*	-0.0314*	-0.0512***	-0.0317*
	(0.0179)	(0.0206)	(0.0179)	(0.0187)	(0.0179)
Chronic obstructive pulmonary disease	-0.0092	0.0099	-0.0087	-0.0069	-0.0091
	(0.0113)	(0.0143)	(0.0113)	(0.0123)	(0.0113)
Depression	0.0191**	0.0221**	0.0187**	0.0223**	0.0190**
	(0.0086)	(0.0098)	(0.0086)	(0.0092)	(0.0086)
Diabetes	0.0318***	0.0286***	0.0318***	0.0303***	0.0318***
	(0.0080)	(0.0094)	(0.0080)	(0.0085)	(0.0080)
Hyperlipidemia	0.0664***	0.0710***	0.0663***	0.0694***	0.0665***
	(0.0075)	(0.0088)	(0.0075)	(0.0080)	(0.0075)
Hypertension	-0.0089	-0.0053	-0.0088	-0.0079	-0.0089
	(0.0077)	(0.0090)	(0.0077)	(0.0082)	(0.0077)
Ischemic heart disease	0.0291**	0.0312*	0.0293**	0.0274*	0.0292**
	(0.0140)	(0.0173)	(0.0140)	(0.0152)	(0.0140)
Obesity	0.1800***	0.1780***	0.1800***	0.1820***	0.1800***
	(0.0089)	(0.0103)	(0.0089)	(0.0093)	(0.0089)
Osteoporosis	0.0193	0.0236	0.0190	0.0161	0.0194
	(0.0145)	(0.0162)	(0.0145)	(0.0155)	(0.0145)
Visit's characteristics					
Visit to own primary care physician	0.0277***	0.0266***	0.0284***	0.0249***	0.0279***
	(0.0074)	(0.0087)	(0.0074)	(0.0079)	(0.0074)
Referred visit	0.0015	-0.0078	0.0013	-0.0063	0.0012
	(0.0178)	(0.0199)	(0.0178)	(0.0187)	(0.0178)

New patient	0.0148	0.0232	0.0157	0.0234	0.0153
	(0.0148)	(0.0171)	(0.0148)	(0.0156)	(0.0148)
Number of visits in last 12 months: (Ref: No visit)					
1 visit in last 12 months	-0.0200	-0.0087	-0.0199	-0.0137	-0.0197
	(0.0136)	(0.0155)	(0.0136)	(0.0143)	(0.0136)
2 visits in last 12 months	-0.0171	-0.0137	-0.0168	-0.0069	-0.0168
	(0.0137)	(0.0157)	(0.0137)	(0.0144)	(0.0137)
3 or more visits in last 12 months	-0.0469***	-0.0400***	-0.0464***	-0.0366***	-0.0465***
	(0.0125)	(0.0142)	(0.0125)	(0.0131)	(0.0125)
Weekend visits	-0.0007	0.0290	-0.0005	0.0083	-0.0008
	(0.0208)	(0.0241)	(0.0208)	(0.0223)	(0.0208)
Seen by other clinicians than MD	0.0551***	0.0573***	0.0547***	0.0524***	0.0547***
	(0.0054)	(0.0063)	(0.0054)	(0.0058)	(0.0054)
Physician characteristics					
Physician specialty: (Ref: General/Family practice)					
Internal medicine	-0.0137**	-0.0127*	-0.0138**	-0.0014	-0.0137**
	(0.0059)	(0.0069)	(0.0059)	(0.0063)	(0.0059)
Ownership: (Ref: Physician or physician group)					
HMO	0.155***	0.192***	0.155***	0.149***	0.155***
	(0.0186)	(0.0209)	(0.0186)	(0.0239)	(0.0186)
Community health center	0.0370***	0.0290***	0.0388***	0.0350***	0.0374***
	(0.0099)	(0.0112)	(0.0099)	(0.0104)	(0.0099)
Medical/Academic health center	0.0426**	0.0904***	0.0433**	0.0626***	0.0425**
	(0.0187)	(0.0205)	(0.0187)	(0.0198)	(0.0187)
Other type of ownership	0.0282***	0.0197*	0.0285***	0.0289***	0.0288***
	(0.0104)	(0.0111)	(0.0104)	(0.0112)	(0.0104)
Solo practice	0.00647	-0.0219***	0.0077	0.0075	0.0066
	(0.0069)	(0.0083)	(0.0069)	(0.0074)	(0.0069)
Employment status: (Ref: Owner)					

Employee	-0.0522***	-0.0518***	-0.0537***	-0.0473***	-0.0526***
	(0.0088)	(0.0096)	(0.0088)	(0.0092)	(0.0088)
Contractor	-0.1040***	-0.1220***	-0.1030***	-0.1100***	-0.1040***
	(0.0130)	(0.0167)	(0.0130)	(0.0140)	(0.0130)
Telephone consults	0.0361***	0.0259***	0.0364***	0.0284***	0.0364***
	(0.0054)	(0.0064)	(0.0054)	(0.0058)	(0.0054)
Physician's incentive for counseling services					
Over 50% of revenue from capitation	0.0352**	0.0302*	0.0351**	0.0088	0.0363**
	(0.0143)	(0.0154)	(0.0142)	(0.0155)	(0.0143)
Over 50% of revenue from managed care contract	-0.0304***	-0.0397***	-0.0315***	-0.0336***	-0.0309***
	(0.0061)	(0.0068)	(0.0061)	(0.0064)	(0.0061)
Over 50% of revenue from case rate	-0.1320***	-0.1710***	-0.1320***	-0.1470***	-0.1320***
	(0.0174)	(0.0177)	(0.0174)	(0.0184)	(0.0174)
Other covariates					
Metropolitan Statistical Area (MSA)	0.0332***	0.0272***	0.0344***	0.0453***	0.0336***
	(0.0079)	(0.0091)	(0.0079)	(0.0083)	(0.0079)
Geographic region: (Ref: Northeast)					
Midwest	-0.0418***	-0.0403***	-0.0412***	-0.0333***	-0.0419***
	(0.0083)	(0.0094)	(0.0083)	(0.0089)	(0.0083)
South	-0.0479***	-0.0451***	-0.0470***	-0.0422***	-0.0475***
	(0.0081)	(0.0091)	(0.0081)	(0.0086)	(0.0081)
West	-0.0150*	-0.0338***	-0.0151*	-0.0154*	-0.0155*
	(0.0085)	(0.0095)	(0.0085)	(0.0089)	(0.0085)
Survey year: (Ref: 2007)					
2008	-0.0330***	-0.0265***	-0.0341***	-0.0327***	-0.0332***
	(0.0073)	(0.0091)	(0.0073)	(0.0079)	(0.0073)
2009	-0.0185**	-0.0108	-0.0199***	-0.0255***	-0.0188**
	(0.0073)	(0.0090)	(0.0073)	(0.0078)	(0.0073)
2010	0.0334***	0.0525***	0.0315***	0.0404***	0.0329***

	(0.0079)	(0.0093)	(0.0080)	(0.0086)	(0.0080)
N	34315	34315	34315	34315	34315

Note: Standard errors are in parentheses.
*** Statistically significant at the 99% level.
** Statistically significant at the 95% level.
* Statistically significant at the 99% level.

[a] Weights were created using the propensity score matching method.
[b] Model (2) & (3) used "visits with full EHR systems" as treated visits and "visits with no or partial EHR systems" as control visits.
[c] Model (4) & (5) used "visits with partial or full EHR systems" as treated visits and "visits with no EHR systems" as control visits.
[d] Model (2) & (4) re-weighted the Raw sample in Model (1) using the propensity score weight.
[e] Model (3) & (5) included the propensity score weight as a covariate in the regression.

Table 2-4: Cumulative/Marginal Impacts of EHR Functionalities/Components on the Probability of Health Behavior Counseling Service Being Delivered

EHR Functions	***Impacts on health behavior counseling service rates (%)***	
(1) Health information and data	Marginal/cumulative impact: (1)	2.3% to 6.1%
(2) Order entry and management	Marginal impact: (2)	3.2% to 5.4%
	Cumulative impact: (1)+(2)	5.5% to 10.9%
(3) Result management without notification system	Marginal impact: (3)	-4.5% to -2.3%
	Cumulative impact: (1)+(2)+(3)	3.2% to 8.6%
(4) Decision support	Marginal impact: (4)	-0.8% to 3.9%
	Cumulative impact: (1)+(2)+(3)+(4)	6.5% to 7.9%
(5) Notification system for abnormal test results ALONE	Marginal impact: (5)	2.7% to 3.8%
	Cumulative impact: (1)+(2)+(3)+(4)+(5)	9.5% to 10.9%

Note:
Marginal impacts and cumulative impacts of different levels of EHR functionalities were obtained by linear combinations of coefficients for each component and interactions estimated from multivariable regressions in Table 2-3.

Table 2-5: Estimated Impact of Electronic Health Record Functionality on the Probability of New Prescription of Bupropion at Visits by Current Smokers

Dependent variable: New Bupropion Prescription	***Raw Sample***	***Sample with Propensity Score Weights [a]***			
		Full EHR vs. No/partial EHR [b]		*Partial/full EHR vs. No EHR [c]*	
		Weighted Sample [d]	*PS weight as a covariate [e]*	*Weighted Sample [d]*	*PS weight as a covariate [e]*
	(1)	(2)	(3)	(4)	(5)
Key independent variables					
Clinical notes	0.0040	-0.0047	0.0043	0.0023	0.0040
	(0.0068)	(0.0052)	(0.0071)	(0.0069)	(0.0068)
Patient problem lists	0.0002	0.0022	0.0003	-0.0002	0.0002
	(0.0049)	(0.0041)	(0.0049)	(0.0046)	(0.0049)
e-Reminder	-0.0017	-0.0053	-0.0018	-0.0010	-0.0017
	(0.0081)	(0.0074)	(0.0081)	(0.0087)	(0.0081)
Clinical notes • e-Reminder	-0.0061	-0.0001	-0.0060	-0.0111	-0.0060
	(0.0108)	(0.0089)	(0.0108)	(0.0127)	(0.0108)
Patient problem list • e-Reminder	0.0173**	0.0237***	0.0173**	0.0253***	0.0173**
	(0.0086)	(0.0075)	(0.0086)	(0.0095)	(0.0086)
Computerized order for prescriptions	-0.0057	-0.0066	-0.0055	-0.0063	-0.0057
	(0.0050)	(0.0049)	(0.0050)	(0.0053)	(0.0051)
Computerized order for laboratory tests	0.0006	0.0035	0.0005	0.0025	0.0006
	(0.0042)	(0.0043)	(0.0042)	(0.0042)	(0.0042)
Viewing imaging results	0.0063*	0.0085**	0.0062*	0.0076**	0.0063*
	(0.0036)	(0.0040)	(0.0036)	(0.0035)	(0.0036)
Viewing laboratory results	0.0044	0.0031	0.0044	0.0067	0.0043

	(0.0057)	(0.0066)	(0.0057)	(0.0067)	(0.0057)
Out of range level highlighted on lab results	-0.0038	-0.0038	-0.0039	-0.0087	-0.0038
	(0.0056)	(0.0074)	(0.0056)	(0.0069)	(0.0056)
Propensity Score Weight (Full EHR vs. No/partial EHR)			-0.0003		
			(0.0011)		
Propensity Score Weight (Full/partial EHR vs. No EHR)					0.0002
					(0.0017)
Patient's characteristics					
Age group: (Ref: Age 18-34)					
Age 35-49	0.0011	0.0006	0.0011	0.0008	0.0011
	(0.0045)	(0.0054)	(0.0045)	(0.0048)	(0.0045)
Age 50-64	-0.0030	-0.0068	-0.0030	-0.0046	-0.0030
	(0.0047)	(0.0055)	(0.0047)	(0.0049)	(0.0047)
Age 65+	-0.0030	-0.0041	-0.0031	-0.0041	-0.0030
	(0.0068)	(0.0074)	(0.0068)	(0.0067)	(0.0068)
Female	-0.0041	-0.0062	-0.0041	-0.0056*	-0.0041
	(0.0030)	(0.0043)	(0.0030)	(0.0033)	(0.0030)
Race/ethnicity: (Ref: White, Non-Hispanic)					
Black, Non-Hispanic	-0.0041	-0.0039	-0.0041	-0.0040	-0.0041
	(0.0034)	(0.0052)	(0.0034)	(0.0037)	(0.0034)
Hispanic	-0.0014	-0.0024	-0.0015	-0.0033	-0.0014
	(0.0051)	(0.0055)	(0.0051)	(0.0045)	(0.0051)
Other race, Non-Hispanic	-0.0041	-0.0048	-0.0041	0.0001	-0.0041
	(0.0051)	(0.0066)	(0.0051)	(0.0068)	(0.0051)
Low-income area	-0.0073**	-0.0059	-0.0073**	-0.0070**	-0.0073**
	(0.0031)	(0.0044)	(0.0031)	(0.0035)	(0.0031)
Higher education area	-0.0008	0.0014	-0.0008	0.0037	-0.0008
	(0.0042)	(0.0054)	(0.0042)	(0.0049)	(0.0042)

Patient's health status					
Major reason for visit: (Ref: New problem)					
Chronic problem (routine)	0.0078**	0.0109**	0.0079**	0.0083**	0.0078**
	(0.0036)	(0.0044)	(0.0036)	(0.0037)	(0.0036)
Chronic problem (flare up)	0.0067	0.0082	0.0068	0.0052	0.0067
	(0.0056)	(0.0055)	(0.0057)	(0.0048)	(0.0057)
Pre/Post surgery	0.0107	0.0030	0.0106	0.0221	0.0107
	(0.0172)	(0.0116)	(0.0171)	(0.0272)	(0.0171)
Preventive care	0.0132**	0.0172***	0.0131**	0.0158***	0.0132**
	(0.0051)	(0.0065)	(0.0051)	(0.0058)	(0.0051)
Other reason for visit	0.0089	0.0215	0.0090	0.0143	0.0089
	(0.0126)	(0.0200)	(0.0126)	(0.0157)	(0.0126)
Related to injury	-0.0049	-0.0036	-0.0048	-0.0041	-0.0049
	(0.0036)	(0.0049)	(0.0036)	(0.0040)	(0.0036)
Chronic conditions:					
1 chronic conditions	0.0019	0.0046	0.0018	0.0022	0.0019
	(0.0043)	(0.0055)	(0.0043)	(0.0046)	(0.0043)
2+ chronic conditions	-0.0017	-0.0025	-0.0018	-0.0016	-0.0017
	(0.0064)	(0.0074)	(0.0063)	(0.0064)	(0.0064)
Arthritis	-0.0070**	-0.0068	-0.0070**	-0.0071**	-0.0070**
	(0.0033)	(0.0044)	(0.0033)	(0.0034)	(0.0033)
Asthma	0.0062	0.0028	0.0061	0.0038	0.0062
	(0.0066)	(0.0058)	(0.0066)	(0.0059)	(0.0066)
Cancer	0.0035	0.0106	0.0034	0.0049	0.0035
	(0.0085)	(0.0138)	(0.0086)	(0.0094)	(0.0085)
Cerebrovascular disease	0.0048	0.0020	0.0048	0.0009	0.0048
	(0.0117)	(0.0077)	(0.0117)	(0.0078)	(0.0117)
Chronic renal failure	-0.0082**	-0.0072*	-0.0083**	-0.0061	-0.0082**
	(0.0037)	(0.0042)	(0.0037)	(0.0039)	(0.0038)
Congestive heart failure	-0.0097**	-0.0129**	-0.0097**	-0.0114***	-0.0097**
	(0.0038)	(0.0054)	(0.0038)	(0.0041)	(0.0038)

Chronic obstructive pulmonary disease	0.0110*	0.0106*	0.0110*	0.0114*	0.0110*
	(0.0059)	(0.0063)	(0.0059)	(0.0062)	(0.0059)
Depression	0.0111**	0.0148**	0.0111**	0.0097**	0.0111**
	(0.0045)	(0.0059)	(0.0045)	(0.0047)	(0.0045)
Diabetes	-0.0044	-0.0045	-0.0044	-0.0045	-0.0044
	(0.0039)	(0.0046)	(0.0039)	(0.0043)	(0.0039)
Hyperlipidemia	-0.0015	-0.0049	-0.0015	-0.0022	-0.0015
	(0.0040)	(0.0043)	(0.0040)	(0.0043)	(0.0040)
Hypertension	0.0011	0.0054	0.0011	0.0041	0.0011
	(0.0035)	(0.0050)	(0.0035)	(0.0037)	(0.0035)
Ischemic heart disease	0.0044	0.0032	0.00445	0.00114	0.00443
	(0.0079)	(0.0099)	(0.0079)	(0.0072)	(0.0079)
Obesity	-0.00301	-0.0019	-0.0030	-0.0001	-0.0030
	(0.0045)	(0.005)	(0.0045)	(0.0053)	(0.0045)
Osteoporosis	-0.0078**	-0.0046	-0.0078**	-0.0068**	-0.0079**
	(0.0031)	(0.0044)	(0.0031)	(0.0034)	(0.0031)
Visit's characteristics					
Visit to own primary care physician	0.0009	0.0038	0.0010	0.0007	0.0009
	(0.0041)	(0.0037)	(0.0041)	(0.0047)	(0.0041)
Referred visit	-0.0027	0.0010	-0.0027	-0.0015	-0.0027
	(0.0040)	(0.0051)	(0.0040)	(0.0044)	(0.0040)
Primary source of payment: (Ref: Private insurance)					
Medicare	-0.0037	-0.0075	-0.0037	-0.0044	-0.0037
	(0.0056)	(0.0057)	(0.0056)	(0.0051)	(0.0056)
Medicaid	-0.0071	-0.0088	-0.0070	-0.0061	-0.0071
	(0.0048)	(0.0056)	(0.0048)	(0.0050)	(0.0048)
Other	-0.0095**	-0.0146***	-0.0095**	-0.0092**	-0.0095**
	(0.0044)	(0.0052)	(0.0044)	(0.0044)	(0.0044)
New patient	-0.0242**	-0.0297**	-0.0241**	-0.0282**	-0.0242**
	(0.0119)	(0.0142)	(0.0119)	(0.0139)	(0.0119)

Number of visits in last 12 months: (Ref: No visit)					
1 visit in last 12 months	-0.0178	-0.0184	-0.0177	-0.0219	-0.0178
	(0.0121)	(0.0152)	(0.0121)	(0.0137)	(0.0121)
2 visits in last 12 months	-0.0148	-0.0228	-0.0148	-0.0210	-0.0148
	(0.0122)	(0.0144)	(0.0123)	(0.0136)	(0.0123)
3 or more visits in last 12 months	-0.0225**	-0.0261*	-0.0224**	-0.0261**	-0.0225**
	(0.0114)	(0.0137)	(0.0114)	(0.0130)	(0.0114)
Weekend visits	-0.0074**	-0.0075	-0.0074**	-0.0060	-0.0074**
	(0.0037)	(0.0046)	(0.0037)	(0.0039)	(0.0037)
Seen by other clinicians than MD	0.0046	0.0069*	0.0045	0.0038	0.0046
	(0.0030)	(0.0039)	(0.0030)	(0.0031)	(0.0029)
Physician characteristics					
Physician specialty: (Ref: General/Family practice)					
Internal medicine	-0.0036	-0.0049	-0.0036	-0.0040	-0.0036
	(0.0030)	(0.0038)	(0.0030)	(0.0032)	(0.0030)
Ownership: (Ref: Physician or physician group)					
HMO	0.0122	0.0077	0.0122	0.0177	0.0123
	(0.0140)	(0.0115)	(0.0140)	(0.0187)	(0.0141)
Community health center	0.0131**	0.0127**	0.0132**	0.0118**	0.0131**
	(0.0054)	(0.0065)	(0.0055)	(0.0060)	(0.0054)
Medical/Academic health center	0.0389**	0.0411	0.0389**	0.0377*	0.0389**
	(0.0194)	(0.0252)	(0.0194)	(0.0205)	(0.0194)
Other type of ownership	0.0093	0.0152*	0.0094	0.0101	0.0093
	(0.0062)	(0.0082)	(0.0062)	(0.0065)	(0.0062)
Solo practice	0.0019	0.0028	0.0020	-0.0003	0.0019
	(0.0042)	(0.0047)	(0.0042)	(0.0041)	(0.0042)
Employment status: (Ref: Owner)					
Employee	-0.0039	-0.0017	-0.0040	-0.0038	-0.0038
	(0.0049)	(0.0056)	(0.0049)	(0.0054)	(0.0049)
Contractor	-0.0049	-0.0058	-0.0047	-0.0030	-0.0049

	(0.0073)	(0.0084)	(0.0073)	(0.0102)	(0.0072)
Telephone consults	0.0076**	0.0058	0.0076**	0.0069**	0.0075**
	(0.0033)	(0.0037)	(0.0033)	(0.0033)	(0.0033)
Physician's incentive on counseling services					
Over 50% of revenue from capitation	-0.0086	-0.0118**	-0.0086	-0.0114**	-0.0087
	(0.0058)	(0.0051)	(0.0058)	(0.0049)	(0.0059)
Over 50% of revenue from managed care contract	0.0006	0.0044	0.0005	0.0041	0.0006
	(0.0037)	(0.0049)	(0.0038)	(0.0041)	(0.0038)
Over 50% of revenue from case rate	-0.0027	-0.0098	-0.0026	-0.0074	-0.0027
	(0.0082)	(0.0072)	(0.0082)	(0.0076)	(0.0082)
Other covariates					
Metropolitan Statistical Area (MSA)	0.00172	0.00272	0.0018	-0.0008	0.0017
	(0.0045)	(0.0048)	(0.0044)	(0.0050)	(0.0045)
Geographic region: (Ref: Northeast)					
Midwest	0.0033	0.0047	0.0034	0.0004	0.0033
	(0.0047)	(0.0045)	(0.0047)	(0.0047)	(0.0047)
South	0.0066	0.0110*	0.0067	0.0056	0.0066
	(0.0050)	(0.0058)	(0.0049)	(0.0055)	(0.0050)
West	-0.0003	0.0044	-0.0003	-0.0023	-0.0003
	(0.0049)	(0.0052)	(0.0049)	(0.0054)	(0.0049)
Survey year: (Ref: 2007)					
2008	-0.0272***	-0.0287***	-0.0273***	-0.0277***	-0.0272***
	(0.0053)	(0.0067)	(0.0053)	(0.0055)	(0.0053)
2009	-0.0303***	-0.0343***	-0.0304***	-0.0311***	-0.0303***
	(0.0051)	(0.0076)	(0.0050)	(0.0055)	(0.0051)
2010	-0.0312***	-0.0331***	-0.0314***	-0.0308***	-0.0312***
	(0.0054)	(0.0073)	(0.0054)	(0.0056)	(0.0054)

N	5536	5536	5536	5536	5536

Note: Standard errors are in parentheses.
*** Statistically significant at the 99% level.
** Statistically significant at the 95% level.
* Statistically significant at the 99% level.

[a] Weights were created using the propensity score matching method.
[b] Model (2) & (3) used “visits with full EHR systems” as treated visits and “visits with no or partial EHR systems” as control visits.
[c] Model (4) & (5) used “visits with partial or full EHR systems” as treated visits and “visits with no EHR systems” as control visits.
[d] Model (2) & (4) re-weighted the Raw sample in Model (1) using the propensity score weight.
[e] Model (3) & (5) included the propensity score weight as a covariate in the regression.

Chapter 3:

The Impact of Electronic Health Records on Hospital-Acquired Adverse Safety Events:

Do Intra-operability and Physician Support Matter?

3.1. Introduction

Information technology is recognized as process innovation that can improve productivity across various service industries (Brynjolfsson and Hitt 2003; Davenport 1993; Stiroh 2002). Health information technology (HIT) such as electronic health records (EHRs) has the potential to improve quality and outcomes of healthcare by innovating process of healthcare delivery (Chaudhry et al. 2006).

Empirically, there has been modest and mixed evidence that EHR improves healthcare quality and outcomes (Buntin et al. 2011; Chaudhry et al. 2006; Goldzweig et al. 2009). The potential benefits accruing to an EHR investment are dependent in part on (1) how well the various EHR components within a hospital interface with each other (intra-operability) and (2) the degree of staff support for, or conversely, resistance against EHR implementation (support). Most prior studies fail to account for intra-operability and staff support when evaluating EHR impact on healthcare quality and outcomes. This study contributes to the literature and federal HIT policy by examining to what extent intra-operability of an EHR system as measured by number of vendor products impacts the magnitude of EHR associated changes in healthcare quality, and whether staff support as measured by physician resistance mediates the effects.

Using a large patient-level administrative data set from California, New York, and Florida for 2009 and 2010, we find that a single source EHR system enhances EHR impact on reducing patient safety events while physician resistance decreases the EHR impact. A single source basic EHR system reduces patient safety events by 19.2%. We do not find statistical evidence for the mediation effect of physician resistance.

3.2. Background

3.2.1. Barriers to EHR Use

While the benefits of HIT are clear in theory and the adoption of EHRs has dramatically increased in response to the incentive program, there are substantial barriers that interfere with implementing and using EHRs effectively to achieve improved quality and outcomes of healthcare. One barrier is the high acquisition and implementation costs of an EHR system (Hersh 2004; Jha et al. 2009; Simon, Rundall, and Shortell 2005) which has been in part alleviated by the EHR incentive program. In addition to the financial burdens, a lack of compatibility between various EHR components and physician resistance are common barriers thought to impact the implementation of EHRs and their effective use (Hersh 2004; Hillestad et al. 2005; Jha et al. 2009; Simon, Rundall, and Shortell 2005). Despite awareness of these barriers to implementation, prior studies have done little to quantify how these barriers influence the impact of EHRs on healthcare quality and outcomes.

Overall, the literature on healthcare quality and outcomes attributable to EHRs has been modest and mixed (Agha 2014; Buntin et al. 2011; Chaudhry et al. 2006; Dranove et al. 2012; Encinosa and Bae 2011; Furukawa, Raghu, and Shao 2010; Goldzweig et al. 2009; McCullough et al. 2010; Miller and Tucker 2011; Parente and McCullough 2009; McCullough, Parente, and Town 2013). One possible explanation for these limited empirical findings is the failure to account for heterogeneous implementation of EHR systems including component compatibility and resistance to adoption.

3.2.2. EHR Use and Patient Safety

The adoption of HIT such as EHRs has potential to improve patient safety and reduce medical errors (Kohn, Corrigan, and Donaldson 1999, 2001; Tang 2003; Bates and Gawande 2003). Improving patient safety and reducing preventable medical errors have been national focus since the Committee on Quality of Health Care in America of the Institute of Medicine (IOM) published a report entitled, "To Err Is Human: Building a Safer Health System." (Kohn, Corrigan, and Donaldson 1999)

Although it has been 15 years since the first IOM report initiating a national focus to reduce medical errors and to improve patient safety, there have been only modest improvements of patient safety and medical errors (Downey et al. 2012; Landrigan et al. 2010; Sukumar et al. 2013; Wachter 2004, 2010). For example, during 1998-2007, there had been a 21% decrease in the national frequency of adverse patient safety events measured by 15 of the Agency for Healthcare Research and Quality's (AHRQ) Patient Safety Indicators (PSIs) (Downey et al. 2012). However, during the period only 7 PSIs (birth trauma injury to neonate, failure to rescue, postoperative hip fracture, obstetric trauma–vaginal without instrument, obstetric trauma–vaginal with instrument, iatrogenic pneumothorax, and postoperative wound dehiscence) decreased whereas 7 PSIs (postoperative pulmonary embolism or deep vein thrombosis, postoperative physiological or metabolic derangement, postoperative sepsis, selected infections due to medical care, decubitus ulcer, accidental puncture or laceration, and postoperative respiratory failure) increased and 1 PSI (postoperative hemorrhage or hematoma) remained unchanged (Downey et al. 2012).

EHRs are one proposed system-wide solution to reduce patient safety events by facilitating and coordinating the process of healthcare (Bates and Gawande 2003; Chaudhry et al. 2006; Kohn, Corrigan, and Donaldson 2001; Tang 2003).

In this study, we examine whether EHR system design and barriers to the adoption and effective use of EHRs influence the impact of EHRs on healthcare quality as measured by hospital-acquired adverse patient safety events.

3.3. Theoretical Framework

The theoretical framework of this study is built upon an IT-enabled process innovation framework by Thomas H. Davenport (Davenport 1993). According to the Davenport's framework, IT improves the productivity and performance of organizations through process innovations. In this study, we consider an EHR system as a tool to innovate processes of healthcare. Our approach examining how EHR system improves healthcare quality and outcomes through process innovation is consistent with previous Health IT studies by Dranove et al. (2012) and McCullough, Parente, and Town (2013).

Compatibility of IT system plays a role in facilitating IT process innovation, and network effects have theoretical implications for compatibility and their impacts on IT process (Hall and Khan 2003; Katz and Shapiro 1985; Kauffman, McAndrews, and Wang 2000; Lee and Mendelson 2007). Network effects are defined as an increase in the value of technology as the number of total users increase. Under the network effects theory, more compatible IT system may promote network benefits and process innovation due to IT by ensuring better communication and coordination as well as economies of scale (Farrell and Saloner 1986; Hall and Khan 2003; Lee and Mendelson 2007).

Compatibility of IT components enhance the process innovation and performance not only across multiple firms but also within a firm (Li and Chen 2012). There are implementation advantages for companies to purchase multiple IT component products from a single vendor, or hardware and software that is compatible with their existing IT system and products. In this study, we focus on compatibility of systems within an organization (intra-operability). In other words, we do not examine how compatibility among EHR systems of different hospitals (inter-operability) influences abilities to share patient health information with other hospitals (e.g. health information exchange), but rather assess to what extent compatibility of EHR system within a hospital moderates potential EHR benefits.

Staff culture such as belief in the benefit of IT facilitate the effective use of IT and help to increase gains from IT process innovation (Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson and Hitt 2000; Hall and Khan 2003). In particular, an organization’s adoption of new process innovation such as EHRs depends on adoption costs and efforts. Hospitals with more positive staff attitudes toward change will face lower barriers to EHR adoption and are more likely to achieve EHR benefits.

3.4. Literature

This study contributes to two streams of literature: (1) compatibility of EHR system and staff support and (2) EHRs and patient safety.

3.4.1. Compatibility of EHR System and Staff Support

Although anecdotal evidence suggests that compatibility accelerates the impact of EHR system on process innovation and quality improvement, the extent of the impact of compatibility has yet to be rigorously investigated (Kellermann and Jones 2013; Taylor et al. 2005). To our best knowledge, no previous empirical works using large patient administrative data have examined how compatibility or intra-operability of EHR system within a hospital affects EHR impacts on healthcare quality and outcomes. On the other hand, a handful of empirical studies have investigated heterogeneous EHR effects by level of staff support for EHR implementation (Avgar, Tambe, and Hitt 2013; Dranove et al. 2012; Litwin 2011; McCullough, Parente, and Town 2013).

Litwin (2011) analyzed the EHR system of Kaiser Permanente health system to estimate the complementary effect of non-physician employees' involvement in configuring, implementing, and encouraging use of their EHR system. The author found that the degree of employee's involvement in the IT effort was positively associated with performance improvement in scheduling office visits.

Dranove et al. (2012) examined whether the relationship between EHR adoption and hospital operating costs varies with complementary factors to optimize an EHR system. They linked EHR adoption data from HIMSS Analytics to the Medicare Hospital Cost Report and estimated the moderating effect of complementary factors measured by hospital's prior IT experience and the availability of IT expertise. The results of multivariate regressions showed that while EHR adoption was initially associated with a slight increase in costs, this initial increase in costs was mitigated by hospital's prior IT experience. They also found that EHR adoption decreased operating costs of hospitals with better availability of IT expertise, but increased operating costs of hospitals with lower availability of skilled IT labor.

Avgar, Tambe, and Hitt (2013) analyzed EHR systems in 15 New York nursing homes to estimate complementary effects of organization's experience with HIT and work practices promoting employee discretion, teamwork, communication, and skill development on problems arising from implementation and use of EHRs. They found that organization's experience with HIT reduce both implementation and usage problems. They also found that work practices encouraging promoting employee discretion, teamwork, and skill development moderated the decrease in usage problems.

Although these prior studies examining heterogeneous EHR effects by staff support for EHR implementation found significant empirical evidences, many of these studies did not analyze common barriers to EHR implementation and their effective use such as physician resistance.

3.4.2. EHRs and Patient Safety

Although an increasing number of studies have analyzed the effect of EHR adoption on patient safety or medical errors, most of these studies have conducted evaluations in a single hospital or in a limited number of hospitals which limited the generalizability of study findings. Additionally, these studies have focused on a medication error or an adverse drug event, which only covers one aspect of patient safety (Ammenwerth et al. 2008; Bates et al. 1999; Chaudhry et al. 2006; King et al. 2003; McKibbon et al. 2012; O'Reilly et al. 2012).

More recently, several state-wide and national studies on the impact of EHR adoption on improving patient safety have been conducted . Culler et al. (2007) analyze the effect of the availability of IT applications on the Agency for Healthcare Research and Quality's (AHRQ) 15 Patient Safety Indicators (PSIs) in 66 Georgia hospitals. The availability of IT application was measured by Computerized Physician Order Entry and IT Infrastructure Survey. Their results demonstrated that the availability of IT application was significantly and negatively associated with only one PSI, postoperative hemorrhage or hematoma.

Menachemi et al. (2007) evaluated the effect of clinical IT adoption on AHRQ's 20 PSIs in 98 Florida hospitals. Their results showed that the clinical IT, which provides information on diagnosis, treatment planning, and evaluation of medical outcomes, decreased only 5 of the PSIs (death in low-mortality DRGs, decreased risk-adjusted rates of decubitus ulcer, decreased risk-adjusted postoperative sepsis, decreased risk-adjusted postoperative hemorrhage, and decreased risk-adjusted postoperative pulmonary embolism).

Amarasingham et al. (2009) analyzed 41 Texas hospitals to estimate the association between the level of hospital automation measured by the Clinical Information Technology Assessment tool and the risk-adjusted complication index consisting of 65 postsurgical and 35 postobstetrical complications. They found that higher scores in decision support were associated with a 16% reduction in the adjusted odds of complications.

Using 4 years of national Medicare patient data, Parente and McCullough (2009) evaluated the effect of 3 health IT applications including Electronic Medical Records (EMRs), nurse charts, and picture archiving and communications systems (PACS) on 3 PSIs: (1) infection due to medical care, (2) postoperative hemorrhage or hematoma, and (3) postoperative pulmonary embolism or deep vein thrombosis. Their panel data analysis shows that only EMRs were associated with improving patient safety and EMRs had a negative and significant effect on just one PSI, infection due to medical care.

Using data on EMR implementation and patient outcomes in California hospitals during 1998-2007, Furukawa et al. (2010) evaluated the effect of EMRs on patient safety complications measured by composite scores of PSIs and inpatient quality indicators (IQIs) developed by AHRQ. The results from their longitudinal analysis demonstrated that EMRs were associated with an increased rate of patient safety complications and a decreased mortality rate.

Encinosa and Bae (2011) examined the effect of EHR use on patient safety, hospital outcomes and costs using patient discharge data of adult surgical patients in 2,619 hospitals. Although they found that EHRs did not decrease patient safety events, EHRs did help to mediate harm due to the patient safety events, reducing mortality, readmission, and costs once patient safety events occur.

Finally, Agha (2014) analyzed Medicare claims data from 1998 to 2005 to estimate the effect of HIT adoption such as electronic patient information and physician notes and clinical decision support such as clinical reminders to physicians. She found that there are insignificant effects of HIT adoption on reducing complications and adverse drug events.

Although a growing number of studies have investigated the effect of EHR on patient safety or medical errors at the state or national level, there appear to be three major limitations in EHR literature on patient safety. First, most of prior studies have evaluated the effect of EHR on only a few patient safety indicators. A handful of studies analyzing the impact of EHR on a more complete set of PSIs have failed to find significant effects (Culler et al. 2007; Encinosa and Bae 2011; Furukawa, Raghu, and Shao 2010).Second, findings from earlier studies were limited to the impact of a specific EHR or a specific EHR component (e.g. CPOE, Decision support). For example, Amarasingham, Plantinga et al. (2009) found negative and significant association between decision support and patient complications, but their finding were limited to decision support, which is just one EHR component. Third, most of earlier studies did not address the problems of endogenous adoption of EHR. One possible reason for the lack of significant findings may stem from the correlation between EHR adoption and PSI outcomes with unobservable hospital or patient characteristics. Using simple OLS regression to estimate these relationships potentially biases the effect of EHR adoptions on PSIs. To address these endogeneity issues, some of the prior studies used panel data analysis (Furukawa, Raghu, and Shao 2010; Parente and McCullough 2009; Agha 2014) or instrumental variable analysis (Encinosa and Bae 2011), but their findings were mixed and weak.

3.4.3. Contribution of This Study

This study advances recent literature on compatibility and complementarities of EHR system by Dranove et al. (2012) and McCullough, Parente, and Town (2013) as well as EHRs and patient safety by Agha (2014), Encinosa and Bae (2011), and Furukawa, Raghu et al. (2010), and Parente and McCullough (2009). Using large patient administrative data, we examine the extent to which common barriers of the implementation and effective usage of EHRs including intra-operability of an EHR system as measured by number of vendor products and staff support as measured by physician resistance affect the impact of EHRs on hospital-acquired adverse patient safety events measured by 15 types of AHRQ PSIs.

We make several contributions. First, to the best of our knowledge, it is the first empirical study analyzing large patient administrative data to estimate the impact of intra-operability of EHR system within a hospital. Second, we contribute to literature by analyzing how physician resistance influences the EHR impact on healthcare quality. Third, we use generalizable measures for both patient safety events (15 types of AHRQ PSIs) and EHR use (basic EHRs consisting of 8 functionalities). We also improve measures of patient safety events by distinguishing between adverse patient safety events occurred during hospitalization with those present on admission (POA). The specific method to identify the hospital-acquired patient safety events is described in more detail in Section 5.2. Finally, we address the endogenous adoption of EHR by employing hospital random and fixed effects models.

3.5. Methods

3.5.1. Data

The study used two data sets. First, the source of patient outcome data is the 2009-2010 Healthcare Cost and Utilization Project (HCUP) State Impatient Databases (SID) for California, New York, and Florida. The HCUP SID is a hospital inpatient administrative database containing principal and secondary diagnoses/procedures, patient demographics, admission/discharge status, total charges, length of stay, and information on the primary payer for each hospital stay (Agency for Healthcare Research and Quality).

Second, the source of EHR data is the Information Technology Supplement to the American Hospital Association's Annual Survey (AHA IT survey) for 2009 and 2010. The survey tracks the adoption of health IT including EHRs. The survey asks participants to report on presence of clinical functionalities of EHR system and the extent of implementation of these functionalities in clinical units. The survey also contains supplementary measures on barriers to implement EHR systems and features of EHR systems. We linked the AHA IT survey to the HCUP SID patient data for California, New York, and Florida.

The unit of observation of this study is any adult surgical patient admission at risk for at least one of the patient safety events measured by 15

AHRQ PSIs. We identify surgical patient discharges using major surgery diagnosis related groups (DRGs) embedded in the patient safety indicator software developed by the Agency for Healthcare Research and Quality (AHRQ PSI software). The AHRQ PSI software defines the population of patients at risk (denominator) for each PSI. We exclude any surgical patient discharges which are not at risk for any of 15 PSIs. However, 98.3% of surgical patient discharges in our sample are at risk for at least one of 15 PSIs. The study sample of this study consists of 2,479,717 observations.

3.5.2. Hospital-Acquired Adverse Patient Safety Events

The primary outcome of this study is a composite measure of hospital acquired adverse patient safety events as listed in Table 1. The adverse patient safety events are measured by 15 patient safety indicators (PSIs) developed by the Agency for Healthcare Research and Quality (AHRQ) based on diagnosis codes (ICD-9-CM). Using present on admission (POA) flags for diagnosis codes, hospital acquired PSI indicators are constructed. Following Houchens, Elixhauser, and Romano (2008), and the HCUP Present on Admission Report, we eliminate hospitals if more than 99 % of their secondary diagnoses were coded as POA, or more than 20% of POA flags for secondary diagnoses were missing (Coffey, Milenkovic, and Andrews 2006; Houchens, Elixhauser, and Romano 2008).

3.5.3. Key Explanatory Variables

The key explanatory variables are (1) basic EHR use, (2) intra-operability of an EHR system, and (3) physician resistance. The degree of intra-operability is measured by whether an EHR system has a single vendor, multiple vendors, or they have a self-developed EHR system. Physician resistance indicates whether hospitals acknowledge “obtaining physician’s cooperation” as one of the barriers to EHR adoption and use. Basic EHR use is a binary variable followed by the three-level definition of EHR adoption developed by Jha, DesRoches et al. (Jha et al. 2009). Basic EHR use is defined as having the following 8 functionalities in at least one major clinical unit: (1) patient demographic information, (2) patient problem lists, (3) medication lists, (4) discharge summaries, (5) laboratory reports viewer, (6) radiology reports viewer, (7) diagnostic test results viewer, and (8) computerized provider order entry (CPOE) for medications.

3.5.4. Empirical Models

To estimate heterogeneous EHR impacts on hospital acquired adverse patient safety events by intra-operability of an EHR system, we use multivariable regression analysis with an interaction term between basic EHR use and intra-operability. The basic specification is of the following form:

$$\text{Patient Safety}_{ijt} = \alpha + \beta_1(\text{Basic EHRs})_{jt} + \beta_2\text{Intra-operability}_{jt} + \beta_3(\text{Basic EHRs}_{jt}) * \text{Intra-operability}_{jt} + \beta_4 D_{jt} + \beta_5 P_{ijt} + \tau_t + \delta_j + \varepsilon_{ijt} \qquad (1)$$

Where **Patient Safety** for patient i in hospital j in year t is a binary indicator equal to one if a surgery admission has any adverse patient safety events during the hospitalization. **Basic EHRs** indicates whether hospitals adopt 8 basic EHR functionalities in at least one major clinical unit. **Intra-operability** is also a binary indicator equal to one if an EHR system has a single vendor or they have a self-developed EHR system. **D** is a vector of hospital characteristics (teaching status, hospital beds, ownership, number of surgical volume) and area characteristics (urban, state fixed effect), and **P** is a vector of patient characteristics (age, gender, race/ethnicity, primary source of payment, median household income) and health status of patients (29 comorbidities). We also include year effects (τ_t).

EHR adoption and hospital-acquired patient safety events are potentially correlated with unobservable characteristics of hospitals. This would bias estimates of the impact of EHRs on patient safety events during hospitalization. To address this issue, we include hospital-specific effect (δ_j), which can be assumed to be random or fixed. We estimate both the hospital random and fixed effects models and use the Hausman test to check the null that hospital random effect estimates are consistent relative to hospital fixed effect estimates (Hausman 1978; Wooldridge 2010).

Additionally, to test whether physician resistance mediates EHR impacts on hospital-acquired adverse patient safety events, we add physician resistance as a predictor in the regression. While the variable on intra-operability of an EHR system is available for 2009-2010, the variable on physician resistance is only available for 2010 because it is missing for more than 90% of sample hospitals in 2009. Because of these data limitations, we estimate the mediation effect of physician resistance using observations in 2010.

All of the regressions were a linear probability model (LPM). We chose the linear probability model because we use interactions between basic EHRs and intra-operability, and interaction terms are complex to interpret in nonlinear models such as probit and logit model(Ai and Norton 2003; Karaca-Mandic, Norton, and Dowd 2012). In addition, as a robustness check, we also estimated all equations using a logit model, and the results for all the major variables were similar to those from the linear probability model. In all regressions, the standard errors are clustered at the hospital level to address the correlation across patient discharges within hospitals.

3.6. Results

Table 2 reports summary statistics for hospital acquired patient safety events, basic EHR use, intra-operability of an EHR system, physician resistance, and other covariates. Column 1 presents the 2009-2010 sample while column 2 contains summary statistics from the sample of 2010 only. In the sample of 2009-2010, 41.7% of adult surgery admissions are in hospitals with basic EHRs, and 1.98% of adult surgery admissions had at least one hospital-acquired patient safety event. In the sample of 2010, adult surgery admissions are characterized with less hospital-acquired patient safety events, but more basic EHRs and intra-operable EHR systems with a single vendor or self-developed system, compared with the 2009-2010 sample.

Table 3 reports the differential estimated impacts of EHRs on hospital acquired adverse patient safety events by intra-operability of an EHR system. Since physician resistance is only available for the sample of 2010, two specifications with different lists of key explanatory variables are estimated for the sample of 2009-2010 (Model A) and 2010 only (Model B). Model (A) only includes basic EHRs, a binary indicator on intra-operability of an EHR system, and its interaction with basic EHRs while Model (B) includes additional indicators on physician resistance as a predictor. Model A using the 2009-2010 sample is estimated via the LPM, random effects, and fixed effects method. Model B using the 2010 sample is estimated via the LPM only, and omits hospital fixed effects because there is only a single observation for each hospital.

Columns 1-3 indicate that estimates from the LPM, random effects, and fixed effects methods are similar. The fixed effects model (column 3) excludes hospital characteristics (teaching status, hospital beds, ownership) and area characteristics (urban, state fixed effect) because there is little (or no) change in these covariates over two years. Basic EHRs with multiple vendors increased hospital-acquired patient safety events. However, the coefficients for the interaction (Basic EHRs * Single vendor/self-developed EHR) were negative and statistically significant, and the magnitude of coefficients on the interaction are greater than magnitude of coefficients on Basic EHRs. This indicates that basic EHRs with single vendor or self-developed EHR system reduce the probability of patient safety events whereas basic EHRs with multiple venders increase patient safety events during hospitalizations. The Hausman test suggests that fixed, rather than random effects, is the appropriate specification since it rejects the null hypothesis that hospital-specific effects are uncorrelated with the regressors and the difference between fixed effect and random effect estimators is not systematic. Specifically, in the fixed effects regression, basic EHRs with single vendor or self-developed EHR system reduced the probability of patient safety events by 0.38 percentage point. This is a substantial relative impact (19.2

percent) since the mean rate of patient safety events in the 2009-2010 sample is 1.98%.

In columns 5, we add an additional indicator on physician resistance to examine the extent to which physician resistance mediates the EHR effects on patient safety events using the 2010 sample only. The change in coefficient on basic EHRs, single vendor/self-developed EHR, and the interaction was minimal between with and without the adjustment for physician resistance (column 4 & 5). These findings indicate that there is no statistical evidence for the mediation effect of physician resistance.

We perform robustness tests to address concerns that estimates on interaction terms may capture individual effects of basic EHRs or intra-operability of an EHR system on patient safety events. To ensure that our estimations are not capturing individual effects but interaction effects, we estimate the effect of (1) basic EHRs only, and (2) basic EHRs and intra-operability of an EHR system without interactions. In table 4, we find that estimates on basic EHRs and intra-operability of an EHR system are insignificant in all these models, which supports robustness of estimates on interactions in table 3.

3.7. Discussion and Conclusion

In this paper, we estimate differential impacts of EHRs on hospital-acquired adverse patient safety events depending on intra-operability of an EHR system and mediation effect of physician resistance on the EHR impacts. We find that intra-operability or compatibility of an EHR system increases EHR effects on reducing patient safety events. A basic EHR system with single vendor or self-developed EHR system reduces patient safety events by 19.2%.

Our finding contributes to the HIT literature by providing robust empirical evidence with large patient administrative data that intra-operability or compatibility of an EHR system promote EHR benefits on improving healthcare quality. We do not find significant mediation effects of physician resistance. Furthermore, McCullough, Parente, and Town (2013) examined the effect of health IT on clinical outcomes, and found HIT benefits are not influenced by complementary organization and technology inputs.

This study also complements the recent EHR studies on improving patient safety (Agha 2014; Amarasingham et al. 2009; Culler et al. 2007; Encinosa and Bae 2011; Furukawa, Raghu, and Shao 2011; Menachemi et al. 2007; Parente and McCullough 2009). While we find that EHRs do not reduce patient safety events on average, a single source basic EHR system reduces patient safety events. It is also important to note that we establish generalizable measures for patient safety events during hospitalization using 15 types of AHRQ PSIs and POA indicators. The main policy implication of this study is that meaningful use of EHRs with appropriate systems guaranteeing compatibility and intra-operability are essential to achieve EHR benefits on improving healthcare quality and outcomes. However, while the CMS EHR incentive program emphasizes inter-operability of EHR systems, and its meaningful use requirement includes ability to exchange clinical information across hospitals and health systems, intra-operability of EHR systems within hospitals is not addressed. Therefore, the results of our study suggest that CMS and policymakers should also consider compatibility of EHR systems as a meaningful use component to guarantee intra-operability of EHR systems within hospitals.

Enogeneity between EHRs and patient safety events would potentially bias the impact of EHRs on patient safety events in both directions. For instance, if high quality hospitals with low patient safety events tend to adopt EHRs, simple OLS would overestimate the impacts of EHRs. On the other hand, hospitals with high-risk patients are more likely to adopt EHRs, simple OLS would underestimate the impact. To address this issue, we estimate both the hospital random and fixed effects models. The Hausman test suggests that fixed effects models over random effects models, which reject the assumption that the unobserved hospital characteristics are uncorrelated with observables. It also aligns with conventional wisdom, that is, characteristics of a hospital and patients in that hospital are correlated. However, differences in the point estimates are small indicating that the bias resulting from failure to account for endogeneous adoption is modest in our sample.

This study has several limitations. First, non-response would have biased our estimates since only 61.7% of adult surgical admissions in California, New York, and Florida during 2009-2010 are linked to the AHA IT survey due to survey nonresponse. Second, information on the diversity and complexity of EHR systems and functionalities used in hospitals in the AHA IT survey was limited. Thus, this study did not capture the effects of unobserved features of EHR systems such as data architecture and end-user interface in different clinical units. Third, although our regressions include a rich set of covariates, unobservable patient and hospital characteristics confounded EHR impacts on patient safety events. However, fixed effects and random effects models allow us to examine whether unobserved characteristics confound the EHR impacts, and our estimates remain robust.

3.8. References

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Table 3-1: Types of Hospital Acquired Patient Safety Events

1. Surgical Only safety events
Foreign body left in during procedure (AHRQ PSI 5)
Postoperative hemorrhage or hematoma (AHRQ PSI 9)
Postoperative wound dehiscence (AHRQ PSI 14)
Postoperative pulmonary embolism or deep vein thrombosis (AHRQ PSI 12)
Postoperative respiratory failure (AHRQ PSI 11)
Postoperative sepsis (AHRQ PSI 13)
Postoperative physiologic and metabolic derangements (AHRQ PSI 10)
Postoperative hip fracture (AHRQ PSI 08)
Death among surgical inpatient with serious treatable conditions (AHRQ PSI 4)
2. Likely procedure safety events
Accidental puncture or laceration during procedure (AHRQ PSI 15)
Iatrogenic pneumothorax (AHRQ PSI 06)
Infection due to medical care (AHRQ PSI 07)
3. Any inpatient safety events
Death in low mortality DRG (AHRQ PSI 2)
Pressure ulcer (AHRQ PSI 03)
Transfusion reaction (AHRQ PSI 16)

Note: Hospital acquired patient safety events are measured by 15 types of patient safety indicators (PSIs) developed by the Agency for Healthcare Research and Quality (AHRQ) based on diagnosis codes (ICD-9-CM) and present on admission (POA) flags.

Table 3-2: Summary Statistics

Variables	***Sample of 2009-2010***	***Sample of 2010***
<u>Dependent/key independent variables</u>		
Hospital Acquired Patient Safety Events	0.0198	0.0183
Basic HER	0.417	0.513
Single vendor/self-developed HER	0.674	0.760
Basic EHR & (Single vendor/self-developed EHR)	0.323	0.400
Physician resistance		0.611
<u>Patient's characteristics</u>		
Age	55.60 (19.50)	55.72 (19.44)
Female	0.605	0.605
Race/ethnicity:		
White, Non-Hispanic	0.619	0.612
Black, Non-Hispanic	0.100	0.106
Hispanic	0.178	0.184
Asian or Pacific Island, Non-Hispanic	0.041	0.039
Other Race, Non-Hispanic	0.061	0.059
Primary source of payment:		
Private insurance	0.374	0.364
Medicare	0.384	0.389
Medicaid	0.157	0.160
Other	0.085	0.088
Median household income for patient's ZIP Code:		
1st quartile	0.241	0.245
2nd quartile	0.250	0.262
3rd quartile	0.277	0.281
4th quartile	0.232	0.212
<u>Patient's health status</u>		
Chronic conditions:		
AIDS	0.001	0.001
Alcohol abuse	0.022	0.022
Deficiency anemias	0.146	0.151
Rheumatoid arthritis/collagen vascular disease	0.020	0.021
Chronic blood loss anemia	0.030	0.031
Congestive heart failure	0.039	0.040
Chronic pulmonary disease	0.134	0.137
Coagulopathy	0.038	0.041
Depression	0.067	0.071
Diabetes without chronic complications	0.155	0.158
Diabetes with chronic complications	0.037	0.039

Drug abuse	0.016	0.016
Hypertension	0.449	0.459
Hypothyroidism	0.088	0.090
Liver disease	0.0200	0.021
Lymphoma	0.005	0.005
Fluid and electrolyte disorders	0.129	0.135
Metastatic cancer	0.025	0.025
Other neurological disorders	0.039	0.040
Obesity	0.101	0.106
Paralysis	0.017	0.018
Peripheral vascular disease	0.058	0.060
Psychoses	0.021	0.023
Pulmonary circulation disease	0.013	0.014
Renal failure	0.078	0.081
Solid tumor without metastasis	0.015	0.015
Peptic ulcer disease excluding bleeding	0.000	0.000
Valvular disease	0.028	0.028
Weight loss	0.029	0.031
Hospital characteristics		
Hospital bedsize	545.7(460.4)	541.8(422.7)
Number of surgical discharges (surgical volume)	8702.9(7312.0)	8484.2(6698.9)
Ownership:		
Not-for-profit	0.730	0.723
For-profit	0.082	0.086
Public	0.188	0.191
Teaching hospital	0.523	0.518
Area characteristics		
Urban	0.538	0.549
California	0.413	0.392
New York	0.277	0.268
Florida	0.310	0.341
Year10	0.480	
Observations	2,479,717	1,103,124

Note: Standard deviations are in parentheses.

Table 3-3: Estimated Impact of EHRs and Intra-operability on Hospital Acquired Patient Safety Events

Dependent variable: Hospital Acquired Patient Safety Events	Sample of 2009-2010			Sample of 2010	
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) OLS
Key independent variables					
Basic HER	0.00287**	0.00171*	0.00206	0.00243+	0.00244+
	(0.00105)	(0.00077)	(0.00147)	(0.00135)	(0.00133)
Single vendor/self-developed EHR	0.00072	0.00004	0.00095	0.00046	0.00041
	(0.00093)	(0.00069)	(0.00091)	(0.00116)	(0.00118)
Basic EHR & (Single vendor/self-developed EHR)	-0.00333**	-0.00256**	-0.00380**	-0.00313*	-0.00305*
	(0.00126)	(0.00093)	(0.00129)	(0.00150)	(0.00150)
Physician resistance					0.00046
					(0.00079)
Patient's characteristics					
Age group: (Ref: Age 18-37)					
Age 38-53	0.00779**	0.00765**	0.00767**	0.00719**	0.00720**
	(0.00033)	(0.00032)	(0.00032)	(0.00045)	(0.00045)
Age 54-65	0.00998**	0.00995**	0.01000**	0.00837**	0.00838**
	(0.00047)	(0.00046)	(0.00046)	(0.00070)	(0.00069)
Age 66-75	0.01156**	0.01178**	0.01187**	0.01092**	0.01093**
	(0.00058)	(0.00055)	(0.00055)	(0.00083)	(0.00083)
Age 76 or older	0.01031**	0.01082**	0.01098**	0.00922**	0.00923**
	(0.00077)	(0.00069)	(0.00069)	(0.00098)	(0.00097)
Female	-0.00123**	-0.00103**	-0.00099**	-0.00073*	-0.00074*
	(0.00027)	(0.00026)	(0.00027)	(0.00037)	(0.00037)
Race/ethnicity: (Ref: White, Non-Hispanic)					
Black, Non-Hispanic	0.00106*	0.00146**	0.00153**	0.00119*	0.00120*

	(0.00051)	(0.00040)	(0.00039)	(0.00056)	(0.00055)
Hispanic	0.00022	0.00069*	0.00081**	0.00067	0.00066
	(0.00034)	(0.00027)	(0.00028)	(0.00041)	(0.00041)
Asian or Pacific Island, Non-Hispanic	0.00048	0.00100+	0.00105*	0.00096	0.00096
	(0.00063)	(0.00053)	(0.00053)	(0.00074)	(0.00074)
Other Race, Non-Hispanic	-0.00007	0.00054	0.00062	-0.00024	-0.00025
	(0.00048)	(0.00041)	(0.00042)	(0.00072)	(0.00073)
Primary source of payment: (Ref: Private insurance)					
Medicare	0.00016	0.00018	0.00022	-0.00010	-0.00010
	(0.00039)	(0.00037)	(0.00037)	(0.00054)	(0.00054)
Medicaid	-0.00069*	-0.00063+	-0.00063+	-0.00130**	-0.00130**
	(0.00031)	(0.00035)	(0.00036)	(0.00043)	(0.00043)
Other	-0.00217**	-0.00203**	-0.00202**	-0.00242**	-0.00240**
	(0.00041)	(0.00040)	(0.00041)	(0.00055)	(0.00055)
Median household income for patient's ZIP Code:					
2nd quartile	-0.00042	-0.00031	-0.00046	-0.00120**	-0.00122**
	(0.00035)	(0.00030)	(0.00031)	(0.00042)	(0.00042)
3rd quartile	-0.00026	-0.00011	-0.00031	-0.00087+	-0.00087+
	(0.00042)	(0.00027)	(0.00027)	(0.00048)	(0.00048)
4th quartile	-0.00030	-0.00052	-0.00075*	-0.00087+	-0.00087+
	(0.00048)	(0.00033)	(0.00034)	(0.00052)	(0.00052)
Patient's health status					
Chronic conditions:					
AIDS	-0.00509+	-0.00523+	-0.00524+	-0.00297	-0.00297
	(0.00288)	(0.00286)	(0.00285)	(0.00442)	(0.00442)
Alcohol abuse	-0.00009	-0.00012	-0.00014	-0.00077	-0.00077
	(0.00092)	(0.00090)	(0.00090)	(0.00120)	(0.00120)
Deficiency anemias	-0.00003	0.00014	0.00013	-0.00071	-0.00071

	(0.00059)	(0.00057)	(0.00057)	(0.00063)	(0.00063)
Rheumatoid arthritis / collagen vascular disease	-0.00087	-0.00112	-0.00116	-0.00090	-0.00090
	(0.00076)	(0.00077)	(0.00077)	(0.00103)	(0.00103)
Chronic blood loss anemia	-0.00110	-0.00100	-0.00097	-0.00106	-0.00105
	(0.00071)	(0.00075)	(0.00075)	(0.00082)	(0.00082)
Congestive heart failure	0.01004**	0.01003**	0.00995**	0.00798**	0.00799**
	(0.00100)	(0.00099)	(0.00099)	(0.00130)	(0.00130)
Chronic pulmonary disease	0.00254**	0.00254**	0.00251**	0.00258**	0.00258**
	(0.00039)	(0.00040)	(0.00040)	(0.00052)	(0.00052)
Coagulopathy	0.04052**	0.04047**	0.04041**	0.03397**	0.03396**
	(0.00198)	(0.00193)	(0.00193)	(0.00198)	(0.00198)
Depression	-0.00129**	-0.00153**	-0.00158**	-0.00157**	-0.00157**
	(0.00046)	(0.00044)	(0.00044)	(0.00060)	(0.00060)
Diabetes without chronic complications	-0.00184**	-0.00193**	-0.00198**	-0.00161**	-0.00161**
	(0.00032)	(0.00031)	(0.00031)	(0.00043)	(0.00043)
Diabetes with chronic complications	-0.00958**	-0.00935**	-0.00932**	-0.01005**	-0.01005**
	(0.00064)	(0.00063)	(0.00064)	(0.00087)	(0.00087)
Drug abuse	0.00063	0.00023	0.00019	0.00220+	0.00220+
	(0.00090)	(0.00092)	(0.00092)	(0.00118)	(0.00118)
Hypertension	-0.00326**	-0.00328**	-0.00328**	-0.00272**	-0.00272**
	(0.00041)	(0.00040)	(0.00040)	(0.00050)	(0.00050)
Hypothyroidism	-0.00173**	-0.00183**	-0.00184**	-0.00116*	-0.00115*
	(0.00042)	(0.00041)	(0.00041)	(0.00058)	(0.00058)
Liver disease	0.00832**	0.00777**	0.00772**	0.00843**	0.00843**
	(0.00137)	(0.00134)	(0.00134)	(0.00181)	(0.00181)
Lymphoma	-0.00433**	-0.00473**	-0.00483**	-0.00522*	-0.00522*
	(0.00155)	(0.00156)	(0.00156)	(0.00228)	(0.00228)
Fluid and electrolyte disorders	0.03211**	0.03214**	0.03219**	0.02922**	0.02921**

	(0.00118)	(0.00117)	(0.00117)	(0.00122)	(0.00122)
Metastatic cancer	0.01265**	0.01202**	0.01183**	0.01110**	0.01111**
	(0.00113)	(0.00101)	(0.00099)	(0.00130)	(0.00130)
Other neurological disorders	0.00375**	0.00371**	0.00367**	0.00274**	0.00275**
	(0.00082)	(0.00080)	(0.00080)	(0.00104)	(0.00104)
Obesity	0.00314**	0.00356**	0.00365**	0.00311**	0.00312**
	(0.00037)	(0.00035)	(0.00035)	(0.00048)	(0.00048)
Paralysis	0.01587**	0.01550**	0.01533**	0.01568**	0.01567**
	(0.00141)	(0.00140)	(0.00140)	(0.00183)	(0.00183)
Peripheral vascular disease	0.00665**	0.00667**	0.00666**	0.00687**	0.00687**
	(0.00080)	(0.00078)	(0.00077)	(0.00107)	(0.00107)
Psychoses	0.00182*	0.00195*	0.00196*	0.00065	0.00065
	(0.00081)	(0.00080)	(0.00079)	(0.00114)	(0.00114)
Pulmonary circulation disease	0.13923**	0.13874**	0.13865**	0.13403**	0.13403**
	(0.00493)	(0.00491)	(0.00490)	(0.00586)	(0.00586)
Renal failure	-0.00062	-0.00062	-0.00063	-0.00179*	-0.00179*
	(0.00060)	(0.00059)	(0.00059)	(0.00090)	(0.00090)
Solid tumor without metastasis	0.00286**	0.00236*	0.00224*	0.00270+	0.00270+
	(0.00104)	(0.00100)	(0.00100)	(0.00147)	(0.00147)
Peptic ulcer disease excluding bleeding	0.01469*	0.01421*	0.01429*	0.01781+	0.01780+
	(0.00674)	(0.00673)	(0.00673)	(0.01019)	(0.01020)
Valvular disease	-0.01032**	-0.01036**	-0.01037**	-0.01065**	-0.01064**
	(0.00096)	(0.00095)	(0.00095)	(0.00125)	(0.00125)
Weight loss	0.05589**	0.05592**	0.05615**	0.04896**	0.04896**
	(0.00355)	(0.00319)	(0.00315)	(0.00359)	(0.00358)
<u>Hospital characteristics</u>					
Hospital bedsize (Ref: >300 beds)					
Small (<100 beds)	-0.00014	0.00146		0.00012	0.00014
	(0.00143)	(0.00152)		(0.00182)	(0.00182)

Medium (100-300 beds)	-0.00114	-0.00049		-0.00125	-0.00118
	(0.00078)	(0.00070)		(0.00079)	(0.00082)
Surgical volume (1000 surgical discharges)	0.00004	0.00027**	0.00006	-0.00004	-0.00004
	(0.00011)	(0.00010)	(0.00093)	(0.00008)	(0.00008)
Ownership: (Ref: Not-for-profit)					
For-profit	-0.00079	-0.00114		-0.00117	-0.00125
	(0.00080)	(0.00094)		(0.00125)	(0.00127)
Public	0.00292**	0.00296**		0.00403**	0.00402**
	(0.00102)	(0.00082)		(0.00118)	(0.00118)
Teaching hospital	0.00403**	0.00179*		0.00382**	0.00388**
	(0.00095)	(0.00077)		(0.00098)	(0.00100)
Area characteristics					
Urban	0.00259**	0.00246**		0.00259**	0.00258**
	(0.00071)	(0.00060)		(0.00074)	(0.00075)
New York	-0.00102	-0.00022		-0.00131	-0.00126
	(0.00078)	(0.00068)		(0.00086)	(0.00086)
Florida	-0.00180+	-0.00089		-0.00239*	-0.00251**
	(0.00094)	(0.00075)		(0.00093)	(0.00090)
Year10	-0.00338**	-0.00307**	-0.00309**		
	(0.00050)	(0.00036)	(0.00038)		
Observations	2,479,717	2,479,717	2,479,717	1,103,124	1,103,124

Note: Standard errors are in parentheses.
** Statistically significant at the 99% level.
* Statistically significant at the 95% level.
+ Statistically significant at the 90% level.

Table 3-4: Robustness Tests

Dependent variable: Hospital Acquired Patient Safety Events	Sample of 2009-2010					
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) RE	(6) FE
Basic EHR	0.00043 (0.00066)	-0.00019 (0.00068)	-0.00065 (0.00120)	0.00051 (0.00065)	-0.00010 (0.00067)	-0.00063 (0.00117)
Single vendor/self-developed EHR				-0.00045 (0.00072)	-0.00070 (0.00059)	-0.00009 (0.00081)
Observations	2,479,717	2,479,717	2,479,717	2,479,717	2,479,717	2,479,717

Dependent variable: Hospital Acquired Patient Safety Events	Sample of 2010		
	(7) OLS	(8) OLS	(9) OLS
Basic EHR	0.00004 (0.00072)	0.00011 (0.00070)	0.00020 (0.00070)
Single vendor/self-developed EHR		-0.00108 (0.00085)	-0.00109 (0.00084)
Physician resistance			0.00056 (0.00079)
Observations	1,103,124	1,103,124	1,103,124

Note: Standard errors are in parentheses.
** Statistically significant at the 99% level.
* Statistically significant at the 95% level.
+ Statistically significant at the 90% level.

Chapter 4:

The Impact of Electronic Health Records on Adherence to Infection-Prevention Process of Care Measures and Surgical Infections

4.1. Background

Improving patient safety and reducing medical errors continues to be a national priority in the United States. In 1999, the Committee on Quality of Health Care in America of the Institute of Medicine (IOM) published a landmark report on patient safety entitled, "To Err Is Human: Building a Safer Health System" estimating that 44,000 - 98,000 patients died in hospitals annually due to preventable medical errors with an associated cost of $17 billion to $29 billion (Kohn, Corrigan, and Donaldson 1999). After the first report in 1999, the IOM also published a couple of subsequent reports on patient safety which not only emphasized benefits of improving patient safety but also concluded that system-wide solutions to improve the healthcare delivery system are required (Aspden et al. 2003; Kohn, Corrigan, and Donaldson 2001).

As one of the system-wide solutions to improve patient safety in surgical care, the Center for Medicare and Medicaid Services (CMS) in partnership with other national organizations instituted the Surgical Care Improvement Project (SCIP) committed to reducing preventable postoperative complications through standardizing surgical protocols (Bratzler and Hunt 2006). In particular, there are 3 core SCIP measures which focus on postoperative infection prevention including (1) the initiation of prophylactic antibiotics within one hour before surgical incision (2 hours if receiving vancomycin) (SCIP-INF-1), (2) the use of prophylactic antibiotics appropriate for the specific procedure the patient is receiving (SCIP-INF-2), and (3) the discontinuation of prophylactic antibiotics within 24 hours after surgery end time (within 48 hours for cardiothoracic surgery) (SCIP-INF-3) (Cataife et al. 2014; Salkind and Rao 2011; Stulberg et al.

2010). These 3 core measures are publically reported on the CMS Hospital Compare website and included in the Value-Based Purchasing (VBP) program which measures the quality of hospital care and rewards hospitals with better quality by adjusting their Medicare payment.

EHR adoption has the potential to reduce patient safety events such as postoperative infections by increasing compliance to surgical guidelines or protocols. In this study, we examine (1) whether EHRs enhance adherence to 3 core SCIP infection-prevention process of care measures and reduce postoperative infections, and (2) adherence to 3 core SCIP measures reduce postoperative infections.

4.2. Conceptual Framework

This study combines a modified version of the Donabedian model (Donabedian 1980) and an EHR adoption model (Abdolrasulnia et al. 2008; Bramble et al. 2010; Kazley and Ozcan 2007; Simon, Rundall, and Shortell 2005, 2007) to evaluate the impact of EHR on postoperative infections through SCIP infection-prevention process of care.

The Donabedian Model of Quality Care consists of system/provider characteristics (structure), the process of medical care, and healthcare quality. The elements of structure include the healthcare system's characteristics (i.e. organization, personnel, specialty mix, financial incentives, patient volume, and access) and provider characteristics (i.e. specialty, financial incentive, belief, and preferences). The process of medical care includes any medical services or products that patients receive involving provider's technical and interpersonal style. In this study, the outcome of healthcare quality is postoperative infections (Donabedian 1980).

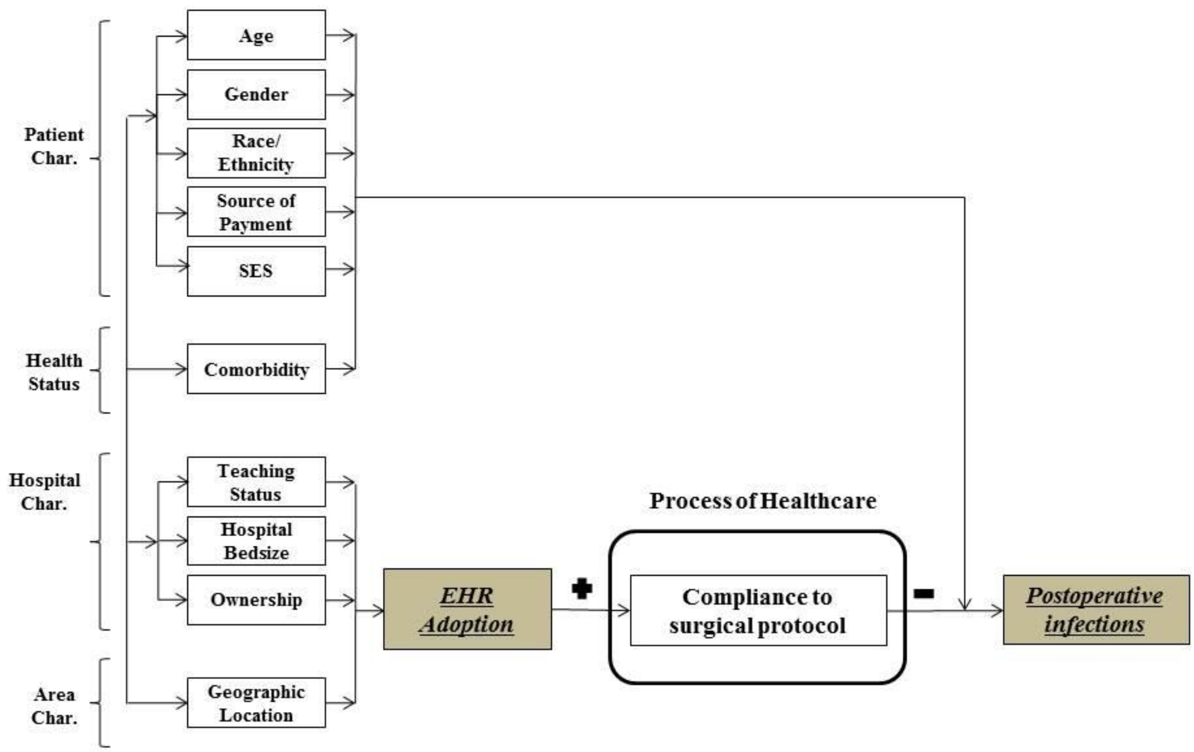
This framework also draws on an EHR adoption model which posits that organizational and market/system characteristics are two principal factors which may affect adoption of EHRs (Kazley and Ozcan 2007; Simon, Rundall, and Shortell 2005, 2007). The organizational characteristics include the size of organization, system affiliation, financial resources, teaching status, and ownership type. Elements of market characteristics include market competition, urban/rural, and any external incentives to improve quality.

In addition to elements from the Donabedian model of healthcare quality and the EHR adoption model, the framework in this study also contains patient characteristics and health status. Patient characteristics include age, gender, race/ethnicity, primary source of payment, socioeconomic status (SES), and health status including comorbidities. Not only do patient characteristics and health status affect patient safety, these two components, which are correlated each other, also are correlated with organizational characteristics, market/system characteristics, and EHR adoption.

EHR adoption influences patient safety mostly through the process of healthcare delivery. According to previous studies investigating the mechanisms through which EHRs affect healthcare quality, the use of EHRs can improve the quality of care by (1) providing clinicians with timely and appropriate patient information, (2) enhancing care coordination, (3) increasing physician compliance to guidelines or a protocol for care, (4) facilitating clinical monitoring through large-scale screening and aggregation of data, (5) improving clinical workflow, (6) improving communication between clinicians and patients as well as among clinicians, and (7) decreasing medication errors or improving medication dosing (Appari, Johnson, and Anthony 2013; Bates and Gawande 2003; Chaudhry et al. 2006; Hillestad et al. 2005; Quinn et al. 2012). In this study, we focus on physician compliance to clinical guidelines operationalized by 3 core SCIP infection-prevention process of care measures on the timely and appropriate use of antibiotics for surgery patients.

Hospital, area, and patient characteristics as well as patients' health status are treated as confounders in this study. Hospital and area characteristics are included as confounders since these two characteristics not only affect the adoption of EHRs but also influence the quality of healthcare. (Donabedian 1980; Kazley and Ozcan 2007; Simon, Rundall, and Shortell 2005). Patient characteristics and patients' health status are also confounders since these two factors influence postoperative infections. Figure 1 is a representation of a conceptual model for the effect of EHRs on postoperative infections.

Figure 4.1: Conceptual Model (The Effect of EHRs on Postoperative Infections)



4.3. Literature Review

Although an increasing number of studies have analyzed the effect of EHR adoption on patient safety, only a handful of empirical studies using large administrative data sets have examined how EHRs improve surgical infection prevention processes and reduce postoperative infections (Appari et al. 2012; Appari, Johnson, and Anthony 2013; Bardhan and Thouin 2013).

Using the CMS Hospital Compare database linked with the Health Information and Management System Society (HIMSS) EHR adoption database for 2004-2006, Bardhan and Thouin (2013) examined the impact of HIT applications on adherence to clinical guidelines including “surgery patients received antibiotics within 1 hour before surgery (SCIP-INF-1)” and “preventive antibiotics stopped for surgery patients within 24 hour after surgery” (SCIP-INF-3). The results from multivariate regressions demonstrated that clinical information system including EMR, clinical decision support, order communication system, and laboratory/image information system increased the overall rate of both SCIP measures.

Using a more recent CMS Hospital Compare database and the HIMSS EHR adoption database, Appari, Carian et al. (2012) and Appari, Johnson et al. (2013) also examined the impact of EHRs on adherence to core SCIP measures. Appari et al. (2012) examined 2010 data to analyze the effect of computerized physician order entry (CPOE) and electronic medication administration records (eMAR) on adherence to clinical guidelines including 3 core SCIP measures. They found that relative to hospitals with neither CPOE nor eMAR, those with both CPOE and eMAR had higher adherence rates to all 3 core SCIP measures while those with eMAR-only were had higher adherence rates to only 2 core SCIP measures (SCIP-INF-1, SCIP-INF-3). Hospitals with CPOE-only were not associated with higher adherence rates to any core SCIP measure. On the contrary, Appari, Johnson, and Anthony (2013) used the same databases for 2006-2010 and found no significant effects of EHRs on increasing adherence rates to SCIP measures.

Although prior studies have provided some empirical evidence for the effectiveness of EHRs in improving surgical infection prevention processes, most of these studies have focused on examining EHR effects on process measures only and have not investigated whether EHRs reduce postoperative infection events. In this study, we address these gaps in literature by examining (1) whether EHRs enhance adherence to 3 core SCIP infection-prevention process of care measures and reduce postoperative infections, and (2) whether adherence to 3 core SCIP measures reduce postoperative infections. To our best knowledge, no previous empirical studies using large patient administrative data have examined how EHRs influence both SCIP infection-prevention process of care and postoperative infection events.

4.4. Methods

4.4.1. Data

The study used three data sets. First, the source of patient outcome data is the 2009-2010 Healthcare Cost and Utilization Project (HCUP) State Impatient Databases (SID) for California, New York, and Florida. The HCUP SID is a hospital inpatient administrative database containing principal and secondary diagnoses/procedures, patient demographics, admission/discharge status, total charges, length of stay, and information on the primary payer for each hospital stay (Agency for Healthcare Research and Quality).

Second, the source of EHR data is the Information Technology Supplement to the American Hospital Association's Annual Survey (AHA IT survey) for 2009 and 2010. The survey tracks the adoption of health IT including EHRs. The survey asks participants to report on presence of specific clinical functionalities and the extent of implementation of these functionalities in clinical units. We linked the AHA IT survey to the HCUP SID patient data for California, New York, and Florida.

Third, we link the 2009-2010 CMS Hospital Compare Database to obtain hospital-level adherence rates to core SCIP infection-prevention process of care measures.

There are two units of observations in this study. At the hospital level, adherence rates for core SCIP measures are examined, and adult surgery patient discharges are examined at the patient level. We identify surgical patient discharges using major surgery diagnosis related groups (DRGs). The sample for this study includes 2,532,422 adult surgery patient discharges.

4.4.2. Postoperative Infections

Postoperative infection events are defined by any adult surgical patient discharge with secondary diagnoses of infected postoperative seroma (ICD-9-CM code: 998.51), other surgical site infection (ICD-9-CM code: 998.59), clostridium difficile enterocolitis (ICD-9-CM code: 008.45), or postoperative pneumonia (ICD-9-CM codes: 481, 482.0-482.9, 483.0-483.8, 485, 486). We exclude any postoperative infection codes indicated as be present on admission (POA). Following Houchens, Elixhauser, and Romano (2008), and the HCUP Present on Admission Report, we eliminate hospitals if more than 99 % of their secondary diagnoses were coded as POA, or more than 20% of POA flags for secondary diagnoses were missing (Coffey, Milenkovic, and Andrews 2006; Houchens, Elixhauser, and Romano 2008).

4.4.3. Core Surgical Care Improvement Project (SCIP) Measures

Hospital-level adherence rates for core SCIP measures (SCIP-INF-1, SCIP-INF-2, SCIP-INF-3) are obtained from the publically available CMS Hospital Compare database. Hospitals report the number of eligible patients and the adherence rate for each SCIP measure. Adherence rates for SCIP measures with less than 25 eligible patients were excluded from the Hospital Compare database.

4.4.4. Basic EHR Use

Basic EHR use is a binary variable followed by the three-level definition of EHR adoption developed by Jha, DesRoches et al. (Jha et al. 2009). Basic EHR use is defined as having the following 8 functionalities in at least one major clinical unit: (1) patient demographic information, (2) patient problem lists, (3) medication lists, (4) discharge summaries, (5) laboratory reports viewer, (6) radiology reports viewer, (7) diagnostic test results viewer, and (8) computerized provider order entry (CPOE) for medications.

4.4.5. Empirical Models

We use multivariate regression analysis to estimate EHR effects on core SCIP measures (Model 1), EHR effects on postoperative infections (Model 2), and the effects of core SCIP measures on postoperative infections (Model 3). To test whether core SCIP measures mediate EHR effects on postoperative infections, we add core SCIP measures as predictors to Model 1 (Model 4). The basic specifications for Model 1-4 are of the following forms:

$$\text{SCIP Measures}_{jt} = \alpha + \beta_1 \text{ Basic EHRs}_{jt} + \beta_2 D_{jt} + \tau_t + \delta_j + \varepsilon_{jt} \quad (1)$$

$$\text{Postoperative Infection}_{ijt} = \alpha + \beta_1 \text{ Basic EHRs}_{jt} + \beta_2 D_{jt} + \beta_3 P_{ijt} + \tau_t + \varepsilon_{ijt} \quad (2)$$

$$\text{Postoperative Infection}_{ijt} = \alpha + \beta_1 \text{ SCIP Measures}_{jt} + \beta_2 D_{jt} + \beta_3 P_{ijt} + \tau_t + \varepsilon_{ijt} \quad (3)$$

$$\text{Postoperative Infection}_{ijt} = \alpha + \beta_1 \text{ Basic EHRs}_{jt} + \beta_2 \text{ SCIP Measures}_{jt} + \beta_3 D_{jt} + \beta_4 P_{ijt} + \tau_t + \varepsilon_{ijt} \quad (4)$$

Where **Postoperative Infection** for patient i in hospital j in year t is a binary indicator equal to one if a surgery admission has any postoperative infection events during the hospitalization. **SCIP Measures** are hospital-level adherence rates to 3 core SCIP infection-prevention performance measures. **Basic EHRs** indicates whether hospitals adopt 8 basic EHR functionalities in at least one major clinical unit. **D** is a vector of hospital characteristics (teaching status, hospital beds, ownership, number of surgical volume) and area characteristics (urban, state fixed effect), and **P** is a vector of patient characteristics (age, gender, race/ethnicity, type of health insurance, median household income) and health status of patients (29 comorbidities). We also include year effects (τ_t). We estimate SCIP measures using ordinary least squares (OLS) model (Model 1) while logistic regressions are used to estimate postoperative infections (Model 2-4). In all regressions, the standard errors are clustered at the hospital level. EHR adoption and SCIP measures are potentially correlated with other unobservable characteristics of hospitals. This would bias estimates of the impact of EHRs on patient safety events during hospitalization. To address this issue, we include hospital-specific effects (δ_j), which can be assumed to be random or fixed. The fixed effects model excludes covariates of teaching status, hospital beds, ownerships, urban status, and state fixed effect since there is little (or no) change in these covariates over two years.

4.5. Results

Table 4-1 reports summary statistics for core SCIP measures, postoperative infection events, basic EHR use, and other covariates. Column 1 presents hospital-level summary statistics while column 2 contains summary statistics from patient/discharge-level sample. 31.0% of hospitals had basic EHRs, and hospital level adherence rates to SCIP-INF-1, SCIP-INF-2, and SCIP-INF-3 are 93.21%, 96.00%, and 91.74% respectively. In patient/discharge level, 40.7% of adult surgery admissions are in hospitals with basic EHRs, and 2.45% of adult surgery admissions had at least one postoperative infection event.

Table 4-2 reports the estimated impact of EHRs on the 3 core SCIP measures. Basic EHRs increase the proportion of patients who receive antibiotics within 1 hour before surgery (SCIP-INF-1) by 1.27 percentage points ($P < .10$), and the proportion of patients whose preventive antibiotics are stopped within 24 hours after surgery (SCIP-INF-3) by 1.93 percentage points ($P<.05$) when estimated using random effects. Basic EHRs have insignificant effect on the proportion of patients who received the right kind of antibiotic to help prevent infection (SCIP-INF-2). The Hausman test suggests that random, rather than fixed effects, is the appropriate specification since it does not reject the null hypothesis that hospital-specific effects are uncorrelated with the regressors and the difference between fixed effect and random effect estimators is not systematic.

Table 4-3 reports the estimated effects of EHRs and core SCIP measures on postoperative infections. The proportion of patients who receive antibiotics within 1 hour before surgery (SCIP-INF-1) is associated with a lower rate of postoperative infections. In particular, the odds ratio (OR) for SCIP-INF-1 is 0.996 ($P<.05$), indicating that for 10 percentage-point increase in the proportion of patients who receive antibiotics within 1 hour before surgery, the odds of having postoperative infections are expected to decrease by 4 percent. However, no statistically significant associations are found between other two core SCIP measures (SCIP-INF-2, SCIP-INF-3) and postoperative infection rates. Basic EHRs have no statistically significant effect on postoperative infection rates with and without the adjustment for 3 core SCIP measures.

4.6. Discussion and Conclusion

In this study, we examine whether EHRs enhance adherence to 3 core SCIP infection-prevention process of care measures and reduce postoperative infections, and whether adherence to 3 core SCIP measures reduce postoperative infections. We find that hospitals with basic EHRs are more likely to adhere to SCIP infection-prevention process measures, specifically timely start and end times for prophylactic antibiotics. An increase in compliance rate to one of the 3 core SCIP measures, timely start of antibiotics, was also associated with lower postoperative infection rates. However, basic EHRs alone have no insignificant effect on postoperative infections.

Our study contributes to the HIT literature by examining the effect of EHRs on healthcare quality as measured by postoperative infections through clinically relevant process of care as measured by SCIP infection-prevention guidelines. However, we find no significant mediation effect of SCIP process of care measures on the association between EHRs and postoperative infections, and no significant EHR effects on postoperative infections. These findings may be attributable to failure to control for unobservable patient, physician, and hospital characteristics due to limitations of the data.

This study has several limitations. First, non-response bias would have biased our estimates since only 61.7% of adult surgical admissions in California, New York, and Florida during 2009-2010 are linked to the AHA IT survey due to survey nonresponse. Second, information on the diversity and complexity of EHR systems and functionalities used in hospitals in the AHA IT survey was limited. Thus, this study did not capture the effects of unobserved features of EHR systems such as data architecture and end-user interface in different clinical units. Third, although our regressions include a rich set of covariates, unobservable patient and hospital characteristics confounded EHR impacts on patient safety events. However, we did perform fixed effects and random effects models in hospital-level regressions to examine whether unobserved hospital characteristics confound the EHR impacts. Future research should further examine clinical relatedness between infection process of care measures and healthcare outcomes and estimate mediation effects of process of care measures on clinically related outcomes.

4.7. Refernces

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Table 4-1: Summary Statistics

Variables	***Hospital Level***	***Patient level***
Dependent/key independent variables		
Postoperative infections	-	0.0245
Core SCIP measures:		
SCIP-INF-1	93.21 (10.63)	93.91 (8.48)
SCIP-INF-2	96.00 (7.98)	95.89 (8.91)
SCIP-INF-3	91.74 (11.01)	92.48 (9.02)
Basic EHR	0.310	0.407
Patient characteristics		
Age	-	55.72 (19.45)
Female	-	0.605
Race/ethnicity:		
White, Non-Hispanic	-	0.616
Black, Non-Hispanic	-	0.099
Hispanic	-	0.177
Asian or Pacific Island, Non-Hispanic	-	0.042
Other Race, Non-Hispanic	-	0.066
Primary source of payment:		
Private insurance	-	0.375
Medicare	-	0.385
Medicaid	-	0.155
Other	-	0.085
Median household income for patient's ZIP Code:		
1st quartile	-	0.240
2nd quartile	-	0.247
3rd quartile	-	0.277
4th quartile	-	0.236
Patient's health status		
Chronic conditions:		
AIDS	-	0.002
Alcohol abuse	-	0.021
Deficiency anemias	-	0.146
Rheumatoid arthritis/collagen vascular disease	-	0.020
Chronic blood loss anemia	-	0.030
Congestive heart failure	-	0.039
Chronic pulmonary disease	-	0.134

Coagulopathy	-	0.038
Depression	-	0.067
Diabetes without chronic complications	-	0.156
Diabetes with chronic complications	-	0.037
Drug abuse	-	0.016
Hypertension	-	0.450
Hypothyroidism	-	0.088
Liver disease	-	0.021
Lymphoma	-	0.005
Fluid and electrolyte disorders	-	0.129
Metastatic cancer	-	0.024
Other neurological disorders	-	0.039
Obesity	-	0.101
Paralysis	-	0.017
Peripheral vascular disease	-	0.059
Psychoses	-	0.021
Pulmonary circulation disease	-	0.013
Renal failure	-	0.078
Solid tumor without metastasis	-	0.015
Peptic ulcer disease excluding bleeding	-	0.000
Valvular disease	-	0.028
Weight loss	-	0.028
Hospital characteristics		
Hospital bedsize	302.7 (266.2)	549.8 (461.0)
Number of surgical discharges (surgical volume)	4149.1 (4403.4)	8872.5 (7391.4)
Ownership:		
Not-for-profit	0.667	0.745
For-profit	0.129	0.081
Public	0.204	0.175
Teaching hospital	0.288	0.518
Area characteristics		
Urban	0.981	0.549
California	0.466	0.427
New York	0.297	0.273
Florida	0.237	0.300
Year10	0.477	0.477
Observations	667	2,532,422

Note: Standard deviations are in parentheses.

Table 4-2: Estimated Impact of EHRs on Core SCIP Measures

Dependent variable:	SCIP-INF-1			SCIP-INF-2			SCIP-INF-3		
	(1) OLS	(2) RE	(3) FE	(4) OLS	(5) RE	(6) FE	(7) OLS	(8) RE	(9) FE
Key independent variables									
Basic EHR	1.266+	1.266+	0.310	0.304	0.292	-0.137	1.964*	1.928*	1.115
	(0.720)	(0.720)	(1.301)	(0.645)	(0.642)	(0.737)	(0.794)	(0.778)	(1.002)
Hospital characteristics									
Bedsize (Ref: >300 beds)									
Small (<100 beds)	0.873	0.873	-	0.869	0.883	-	-0.633	-0.666	-
	(1.358)	(1.358)	-	(1.144)	(1.137)	-	(1.844)	(1.855)	-
Medium (100-300 beds)	-0.095	-0.095	-	0.630	0.642	-	-0.118	-0.127	-
	(1.143)	(1.143)	-	(1.049)	(1.043)	-	(1.177)	(1.161)	-
Surgical volume	0.116	0.116	-1.548	0.084	0.084	-0.294	0.097	0.092	-0.943
(1000 surgical discharges)	(0.099)	(0.099)	(1.066)	(0.071)	(0.071)	(0.401)	(0.085)	(0.084)	(0.663)
Ownership: (Ref: Not-for-profit)									
For-profit	0.097	0.096	-	0.083	0.055	-	-1.718	-1.783	-
	(1.343)	(1.343)	-	(1.451)	(1.461)	-	(1.866)	(1.852)	-
Public	0.143	0.143	-	0.496	0.498	-	-1.869	-1.863	-
	(1.026)	(1.026)	-	(0.675)	(0.674)	-	(1.546)	(1.549)	-
Teaching hospital	-0.665	-0.665	-	-0.739	-0.744	-	-0.304	-0.306	-
	(1.371)	(1.371)	-	(1.036)	(1.042)	-	(1.117)	(1.122)	-
Area characteristics									
Urban	4.188	4.189	-	-3.347**	-3.337**	-	-5.948**	-6.042**	-
	(7.011)	(7.012)	-	(0.613)	(0.609)	-	(2.206)	(2.164)	-
New York	2.700*	2.700*	-	0.434	0.431	-	1.912*	1.903*	-
	(1.070)	(1.070)	-	(0.514)	(0.513)	-	(0.834)	(0.830)	-
Florida	3.681**	3.682**	-	-0.693	-0.681	-	2.619*	2.654*	-
	(0.927)	(0.927)	-	(1.192)	(1.188)	-	(1.278)	(1.267)	-
Year10	5.481**	5.481**	6.382**	-0.248	-0.248	-0.222	1.753*	1.786*	2.420*
	(0.761)	(0.761)	(1.038)	(0.620)	(0.621)	(0.828)	(0.831)	(0.834)	(1.082)
Observations	627	627	627	626	626	626	626	626	626

Note: Standard errors are in parentheses.
** Statistically significant at the 99% level; * Statistically significant at the 95% level; + Statistically significant at the 90% level.

Table 4-3: Estimated Impact of EHRs and Core SCIP Measures on Postoperative Infections (Odd ratios)

Dependent variable: Postoperative Infections	(1) Logistics	(2) Logistics	(3) Logistics
Key independent variables			
Basic EHR	-	0.98955	0.98370
	-	(0.04169)	(0.04040)
Core SCIP measures:			
SCIP-INF-1	0.99638*	-	0.99634*
	(0.00164)	-	(0.00163)
SCIP-INF-2	0.99742	-	0.99727
	(0.00336)	-	(0.00337)
SCIP-INF-3	1.00273	-	1.00289
	(0.00347)	-	(0.00345)
Patient characteristics			
Age group: (Ref: Age 18-37)			
Age 38-53	1.64496**	1.64562**	1.64521**
	(0.05937)	(0.05924)	(0.05931)
Age 54-65	2.03445**	2.03518**	2.03507**
	(0.09850)	(0.09819)	(0.09832)
Age 66-75	2.16285**	2.16199**	2.16368**
	(0.10966)	(0.10907)	(0.10947)
Age 76 or older	2.34736**	2.34594**	2.34816**
	(0.12987)	(0.12951)	(0.12979)
Female	0.72908**	0.72894**	0.72907**
	(0.01169)	(0.01170)	(0.01169)
Race/ethnicity: (Ref: White, Non-Hispanic)			
Black, Non-Hispanic	1.00776	1.00533	1.00786
	(0.02354)	(0.02339)	(0.02351)
Hispanic	0.98623	0.98293	0.98566
	(0.02730)	(0.02723)	(0.02752)
Asian or Pacific Island, Non-Hispanic	1.02304	1.02165	1.02293
	(0.03398)	(0.03327)	(0.03400)
Other Race, Non-Hispanic	0.99168	0.99013	0.99194
	(0.02756)	(0.02762)	(0.02744)
Primary source of payment: (Ref: Private insurance)			
Medicare	1.12988**	1.13086**	1.13002**
	(0.02679)	(0.02677)	(0.02673)

Medicaid	1.25347**	1.25368**	1.25309**
	(0.03219)	(0.03228)	(0.03220)
Other	1.04667	1.04589	1.04638
	(0.03508)	(0.03497)	(0.03500)
Median household income for patient's ZIP Code:			
2nd quartile	0.97576	0.97430	0.97536
	(0.02053)	(0.02054)	(0.02034)
3rd quartile	0.97612	0.97383	0.97583
	(0.02513)	(0.02495)	(0.02496)
4th quartile	0.94186*	0.94063*	0.94146*
	(0.02874)	(0.02887)	(0.02850)
Patient's health status			
Chronic conditions:			
AIDS	1.40902**	1.41240**	1.41005**
	(0.09170)	(0.09168)	(0.09168)
Alcohol abuse	1.45077**	1.45043**	1.45073**
	(0.03779)	(0.03770)	(0.03775)
Deficiency anemias	1.28834**	1.28822**	1.28799**
	(0.02741)	(0.02748)	(0.02740)
Rheumatoid arthritis/collagen vascular disease	1.02055	1.02090	1.02072
	(0.02765)	(0.02765)	(0.02766)
Chronic blood loss anemia	1.18570**	1.18592**	1.18581**
	(0.04103)	(0.04115)	(0.04104)
Congestive heart failure	2.16483**	2.16655**	2.16519**
	(0.04400)	(0.04410)	(0.04393)
Chronic pulmonary disease	1.55052**	1.55016**	1.55024**
	(0.02677)	(0.02680)	(0.02678)
Coagulopathy	1.99004**	1.98839**	1.98967**
	(0.06241)	(0.06243)	(0.06242)
Depression	1.01791	1.01817	1.01800
	(0.02057)	(0.02057)	(0.02057)
Diabetes without chronic complications	0.97312	0.97297	0.97285
	(0.01780)	(0.01784)	(0.01786)
Diabetes with chronic complications	0.92928**	0.92893**	0.92989**
	(0.01926)	(0.01907)	(0.01901)
Drug abuse	1.26566**	1.26459**	1.26582**
	(0.04424)	(0.04416)	(0.04418)
Hypertension	0.85319**	0.85323**	0.85311**
	(0.02306)	(0.02306)	(0.02306)
Hypothyroidism	0.92546**	0.92539**	0.92537**

	(0.01609)	(0.01615)	(0.01610)
Liver disease	1.08548**	1.08667**	1.08601**
	(0.02505)	(0.02498)	(0.02502)
	1.25499**	1.25535**	1.25540**
Lymphoma	(0.06118)	(0.06120)	(0.06116)
	3.65277**	3.65208**	3.65135**
Fluid and electrolyte disorders	(0.09588)	(0.09542)	(0.09544)
	1.67010**	1.66957**	1.67022**
Metastatic cancer	(0.04385)	(0.04395)	(0.04386)
	1.43371**	1.43378**	1.43357**
Other neurological disorders	(0.02804)	(0.02810)	(0.02807)
	1.11339**	1.11206**	1.11336**
Obesity	(0.02497)	(0.02507)	(0.02497)
	2.02795**	2.02863**	2.02799**
Paralysis	(0.06045)	(0.06048)	(0.06045)
	1.12335**	1.12319**	1.12352**
Peripheral vascular disease	(0.02133)	(0.02149)	(0.02132)
	1.38935**	1.38953**	1.38979**
Psychoses	(0.03544)	(0.03552)	(0.03539)
	1.75189**	1.75213**	1.75215**
Pulmonary circulation disease	(0.04421)	(0.04420)	(0.04419)
	1.12756**	1.12762**	1.12781**
Renal failure	(0.02178)	(0.02173)	(0.02175)
	1.20729**	1.20644**	1.20735**
Solid tumor without metastasis	(0.03709)	(0.03713)	(0.03709)
	1.76818**	1.76294**	1.76714**
Peptic ulcer disease excluding bleeding	(0.29907)	(0.29807)	(0.29914)
	0.90721**	0.90695**	0.90732**
Valvular disease	(0.02242)	(0.02241)	(0.02242)
	3.46055**	3.45852**	3.46251**
Weight loss	(0.12799)	(0.12851)	(0.12847)
	1.40902**	1.41240**	1.41005**
<u>Hospital characteristics</u>			
Hospital bedsize (Ref: >300 beds)			
Small (<100 beds)	0.89571	0.88584	0.89486
	(0.08555)	(0.08451)	(0.08592)
Medium (100-300 beds)	0.95589	0.95383	0.95677
	(0.04885)	(0.04874)	(0.04874)
Surgical volume (1000 surgical discharges)	1.00674+	1.00688+	1.00696+
	(0.00375)	(0.00382)	(0.00379)

Ownership: (Ref: Not-for-profit)			
For-profit	1.03644	1.04072	1.03760
	(0.06573)	(0.06505)	(0.06581)
Public	1.28646**	1.29609**	1.29117**
	(0.07264)	(0.07417)	(0.07289)
Teaching hospital	1.13819*	1.14340*	1.13977*
	(0.06403)	(0.06487)	(0.06457)
Area characteristics			
Urban	1.03294	1.03504	1.03221
	(0.04841)	(0.04910)	(0.04834)
New York	1.13644*	1.13036*	1.13590*
	(0.06920)	(0.06915)	(0.06919)
Florida	0.96569	0.95969	0.96596
	(0.05451)	(0.05287)	(0.05461)
Year10	0.94517*	0.93469**	0.94850+
	(0.02399)	(0.02358)	(0.02664)
Observations	2532422	2532422	2532422

Note: Standard errors are in parentheses.
** Statistically significant at the 99% level.
* Statistically significant at the 95% level.
+ Statistically significant at the 90% level.

Chapter 5:

Conclusion

5.1. Summary of Principal Findings

The main objective of this dissertation is to examine the impact of EHR use on health services utilization and quality of healthcare both in ambulatory and hospital care settings. This dissertation addressed 5 major gaps in the existing literature: 1) effectiveness of specific EHR functionalities and their mechanisms, 2) impact of EHR system intra-operability, 3) impact of physician resistance, 4) valid specification of the quality of care and outcomes measures, and 5) unobserved confounding related to EHR adoption.

The first essay examines the impact of eight EHR components that map four core EHR functionalities on the frequency of health behavior counseling provided during primary care visits. This essay found that two functionalities, order entry and health information and data were independently associated with increases in the probability of health behavior counseling service delivery. On the other hand, decision support and results management, were associated with decreases in the provision of health behavior counseling services when these components were used alone. However, using these two functionalities with relevant complementary components increase health counseling services. Finally, the findings of this essay also support the existence of information overload due to lab and image result viewers and information overload is addressed by relevant notification for critical lab or imaging results.

The second essay examines differential impacts of EHRs on hospital acquired adverse patient safety events depending on intra-operability of an EHR system and the degree of physician resistance. The main conclusion of this essay is that a single source EHR system is associated with a reduction in patient safety events. However, I do not find significant mediation effects of physician resistance.

The third essay examines whether EHRs enhance adherence to the 3 core SCIP infection-prevention process of care measures and reduce postoperative infections. I find that hospitals with basic EHRs are more likely to adhere to SCIP infection-prevention measures, and an increase in adherence rates of one of the 3 core SCIP measures are associated with lower postoperative infection rates. Specifically, basic EHRs help clinicians follow clinical guidelines on timely start and end times for antibiotic use for surgery patients. However, I find no significant mediation effect of SCIP process of care measures on the association between EHRs and postoperative infections, and no significant EHR effects on postoperative infections.

5.2. Implications of Findings

The present dissertation suggests two key implications to policy makers and health services researchers. The principal implication is that policies should support the adoption of EHRs with appropriate functionalities. Specifically, findings of the first essay suggest that core EHR functionalities combined with complementary components are essential for improving outpatient primary care processes. The second essay suggests that compatibility and intra-operability of EHR systems within hospitals are essential for improving healthcare quality and outcomes in inpatient care.

The second implication of this dissertation is that appropriate measures of EHR system design and functionalities as well as better specification of the quality of care measures potentially improved by EHR use are required in order to rigorously evaluate the impact of EHRs. The first essay uses direct measures for eight EHR components that may potentially promote health behavior counseling services and estimates the impact of specific elements of the EHR system on health behavior counseling services. Moreover, it also examine whether specific EHR elements supplement or are necessary in combination with other elements. The second essay establishes generalizable and appropriate measures of patient safety events by identifying patient safety events which occur during hospitalization. The third essay uses infection process of care measures and postoperative infection measures to examine clinical relatedness between infection process of care measures and postoperative infections.