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ABSTRACT

Health information technology (IT) adoption, it is argued, will dramatically improve patient care. We study the impact of hospital IT adoption on patient outcomes focusing on the roles of technological and organizational complements in affecting IT's value and explore underlying mechanisms through which IT facilitates the coordination of labor inputs. We link detailed hospital discharge data on all Medicare fee-for-service admissions from 2002-2007 to detailed hospital-level IT adoption information. We employ a difference-in-differences strategy to identify the parameters of interest. For all IT sensitive conditions we find that health IT adoption reduces mortality for the most complex patients but does not affect outcomes for the median patient. This implies that the benefits from IT adoption are skewed to large institutions with a severe case mix. We decompose the impact of health IT into care coordination, clinical information management, and other components. The benefits from health IT are primarily experienced by patients whose diagnoses require cross-specialty care coordination and extensive clinical information management.

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1 Introduction

The US health care system is often criticized as fragmented and uncoordinated. The consequences of this poorly integrated system are stark, leading to a large number of preventable medical errors and wasteful resource allocation. The cost of medical errors are famously large with some estimates attributing over 44,000 deaths annually to inpatient hospital errors (IOM, 1999). Faced with a health care system that appears far from optimized many health policy analysts have placed the diffusion of health information technology (IT) as the centerpiece of their program to improve care continuity and coordination (IOM, 1999, 2001; Buntin et al., 2011). Recent improvements in health IT and the growth of IT investments in other sectors of the economy suggest that health IT can dramatically improve the practice of medicine.

The potential for health IT to transform health care has placed it near the top of the health policy agenda. Presidents from both parties made health IT a budgetary priority.[1] The recent HITECH Act (2009) commits an estimated $34 billion in subsidies for private health care providers to adopt and utilize health IT systems. While health IT's potential is clear, these technologies are not without their critics and the ultimate economic and clinical impact of widespread health IT adoption remains uncertain.[2]

In this paper, we analyze the impact of hospitals' adoptions of different types of health IT applications on the outcomes of millions of Medicare patients. Our data span a period of rapid IT adoption. The volume and quality of our data allow us explore heterogeneity in IT's impact across organizations and patients which, in turn, illuminates the underlying mechanisms through which health IT acts.

This study contributes to a growing economic literature on the value and impact of IT. Information technologies have reduced the costs of coordinating production, communication, and information processing, leading to a substantial increase in productivity (Stiroh, 2002;

[1]In his January 3, 2009 radio address, President Obama stated, "We will update and computerize our health care system to cut red tape, prevent medical mistakes, and help reduce health care costs by billions of dollars each year."

[2]Black et al. (2011), for example, provide a broad review of the literature and suggest that the relationship between IT and health care quality is unclear.

Brynjolfsson and Hitt, 2003). However, the benefits of IT are not evenly distributed across organizations as the gains from these technologies depend upon both organizational and labor complementarities (Brynjolfsson and Hitt, 2002). For example, Bartel et al. (2007) find that IT-enabled manufacturing equipment increased productivity, dramatically increased product customization, and increased machine operator skill levels. Bloom et al. (2012) find that the US-based firms operating in the UK earned higher returns from IT investments than non-US based firms. These high returns are a consequence of US firms' internal organizational structures that complemented IT investments. Similarly, Autor et al. (1998) uncover strong evidence of skill-biased IT and labor complementarity. Other studies emphasize the role of task-level complementarities between IT and and labor inputs (Hubbard, 2003; Baker and Hubbard, 2003; Autor et al., 2003; Acemoglu and Autor, 2011).

Health care is an interesting environment to study the roles of organizational and task-based complementarities in IT. Each patient's diagnoses represent a set of tasks which may be suited to guideline-based decision support or may require different levels of information management and care coordination. We use very detailed patient-level data to estimate the impact of hospital IT adoption on patient outcomes (mortality, length-of-stay, and hospital readmission) focusing on the role of heterogeneity along both organizational and patient domains. Like many other sectors of the economy, the health care sector has also expanded its reliance on IT over the last two decades.[3] The increasing importance of IT is not surprising. Healthcare production requires the management, coordination, and communication of large amounts of information and these tasks are precisely what information systems are designed to facilitate. Many health care policy commentators contend that electronic medical record (EMR) technologies will transform medicine by facilitating better and more coordinated care. Health IT may also enable the creation of new provider systems like Accountable Care Organizations (ACOs) (Hillestad et al., 2005; Buntin et al., 2010). However, the ability of health IT to transform medicine likely depends upon how IT performs in a specific organizational context and the underlying mechanisms through which it affects outcomes. It is those

[3]Lee et al. (2012) document that from 1997 to 2007, California hospitals increased the stock of health IT capital by 180%– a much greater increase than conventional capital and labor inputs.

questions that we address in this paper.

Hospitals utilize many different types of health information technologies. These systems are based on a core set of complementary applications. The electronic medical record (EMR) provides the foundation for health information systems. EMRs systematically collect patients' health information replacing traditional medical charts. Computerized provider order entry (CPOE) capabilities allow providers to electronically enter medical orders for patient services and medications. Through direct physician order entry, CPOE reduces opportunities for miscommunication between disparate care providers. These technologies also serve as a platform for decision support functions which may reduce prescribing errors and improve clinical guideline compliance. Our analysis primarily (but not exclusively) focuses on these core clinical applications.

Health IT's value may depend upon organizational and technological complements as well as the information content of tasks. EMR systems may be used to automate standardized treatment guidelines and implement rules-based procedures to prevent common errors. This combination of technological and organizational capabilities is commonly referred to as "Meaningful Use" - these guideline mechanisms are emphasized in both the policy and informatics literatures. If this aspect of health IT is important, then adoption should yield expected outcome improvements across the general inpatient population. Health IT might also facilitate complex decision-making and communications problems.[4] In particular, health IT may help manage patients with particularly difficult clinical data management problems. Similarly, health IT may help coordinate care for patients being treated by multiple clinical specialties where communication between providers can be important and in practice is often less than necessary to achieve the best patient outcomes. If these aspects of IT are important, then adoption should affect outcomes for patients for which communication and/or information management is most important.

We acquire detailed, hospital-level, health IT adoption information from the Health Information Management System Society (HIMSS) for all general, acute care, non-federal US

[4]This distinction between rules-based guideline effects and complex decision making is similar to the framework described by Autor et al. (2003).

hospitals from 2002-2007, a period of rapid technology diffusion. These data are merged with hospital organization and location information from the American Hospital Association. The number of hospitals adopting EMR increased from 16% to 33% while CPOE increased from 1% to over 16% over this time frame. These data contain information on the types and timing of information systems installed by the organization. We merged the hospital IT adoption data to inpatient discharge records on every Medicare, fee-for-service (FFS) patient admitted for one of four high-mortality conditions we study – acute myocardial infarction (AMI), congestive heart failure (CHF), coronary atherosclerosis (CA), and pneumonia. These data are large with over 6,600,000 observations. We view AMI as a control diagnoses for these analysis capturing time varying changes to hospital quality initiatives that may be correlated with IT adoption. AMI is condition for which EMR adoption is unlikely to directly impact outcomes as its widely accepted diagnostic and treatment protocols require rapid execution with limited time for interaction with information systems.

The discharge data contain detailed information on patients' demographics, comorbidities, types of services, and procedures provided. We use these data to construct patient severity measures. Patient severity is then decomposed into components that capture the information management and coordination requirements resulting from each patient's diagnoses. Decomposing these information and coordination requirements allows us a deep look into the mechanisms though which IT effects the clinical production process. We use a difference-in-difference identification strategy to remove unobserved hospital heterogeneity that may be correlated with both health IT adoption and patient outcomes.[5]

Our parameter estimates suggest that health IT does not affect patient outcomes for patients with mean severity. We examine whether this null findings is the result of uncontrolled differences in hospitals' uses of IT (as measured by Meaningful Use) or the adoption of complementary technologies. Neither the adoption of complimentary technologies nor complying with Meaningful Use standards affect patient outcomes. These results imply that automated treatment guidelines and rules-based decision support systems have limited clinical benefits

[5]Our estimates indicate that the bias from this type of endogeneity is modest - a result that is consistent with McCullough et al. (2010) and Agha (2011).

for the outcomes and conditions of the average patient.

If health IT principally affects the health production process through better clinical data management and/or reducing the cost of coordinating care across providers, then health IT adoption should affect outcomes for the most severely ill. We test this proposition and find that the impact of IT is increasing in patient severity, reducing mortality for the highest risk patients for all conditions except our control condition, AMI. These effects are precisely estimated and are robust to multiple refutation tests. We also explored potential complementarities between health IT and the information content of tasks at a patient level. We find strong evidence that IT adoption reduces mortality for those pneumonia patients requiring more care coordination and those with greater information management requirements. For the other conditions we study, the parameter estimates are not as precisely estimated but nonetheless hint that health IT similarly affects high-severity patients by facilitating cross-provider communication and helping hospital staff manage clinical information. Accounting for this heterogeneous response, our parameter estimates imply that across our IT sensitive diagnoses, mortality falls by a modest 200 deaths per 100,000 admissions after a hospital adopts both EMR and CPOE. Importantly, the benefits of IT adoption skew towards larger hospitals with a more severe case mix.

The detail in our data allows us to address several other longstanding questions on the impact of IT adoption. In other contexts, network externalities have been found to affect technology adoption directly, through interoperable technologies, and indirectly through learning spillovers. One important justification for the broad role of the federal government in promoting health IT adoption is the presence of network externalities. If there are network effects in hospital IT adoption they are almost surely local as health care is, in general, locally delivered. We test for the presence of network effect by estimating the impact of neighboring hospitals' IT adoptions on patient outcomes controlling for unobservable and time-invariant hospital heterogeneity. Here we find no evidence for network externalities in hospital IT adoption. The literature has also emphasized the role of technological improvements which may deter adoptions of current technologies as organizations delay adoption waiting for better technologies to become available in the future as well as the importance of organizational learning following IT adoption. We find no evidence that the later adoption leads to better mean outcomes or meaningful IT learning effects, nor do we find that compliance with Meaningful Use affects mean patient outcomes.

The role of health IT is the focus of a large literature that principally relies on pre-post designs from the adoption by large, academic centers. In general, these studies find a large impact of IT adoption.[6] However, these large effects have not been found in the more modest number of econometric analyses estimating the impact of health IT across a large number of hospitals. Our work is most closely related to McCullough et al. (2010), Agha (2011) and Miller and Tucker (2011). McCullough et al. (2010) and Agha (2011) estimates the impact of IT adoption using a hospital-level panel where the principle dependent variables are process quality and mortality respectively. They find that IT has little or no impact on average hospital quality. Miller and Tucker (2011) link birth certificate records to county-level health IT adoption rates and find that increased health IT penetration is associated with a modest but meaningful decline in infant mortality rates.[7] Dranove et al. (2012) find considerable heterogeneity in the impact of health IT adoption on hospital cost structure. The relative contribution of our work is the focus on the heterogeneous responses across patients and organizations to IT adoption which is central to understanding both the impact of IT and the underlying mechanisms.

The remainder of the paper is organized as follows. The next section discusses the contextual background of health IT and describes in detail the mechanisms through which health IT can impact patient outcomes. Section 3 describes the data and the adoption patterns and summary statistics are presented in Section 4. Section 5 presents our results and Section 6 concludes.

[6] Buntin et al. (2011) provides a recent review of this large literature.

[7] Athey and Stern (2002) provide an early study of IT and health quality, they found that Enhanced 911 system adoption decreased both mortality and costs in emergency medicine.

2 Background and Mechanisms

While hospitals have employed IT since the 1960s (Borzekowski, 2002), it is only during the past decade that clinical activities have been widely automated. The Electronic Medical Record (EMR) is the foundation of these new health information systems. The EMR replaces traditional paper charts and documents a wide range of patient and diagnostic information. EMRs also capture crucial clinical data such as prescriptions and lab results. EMR adoption is, ideally, accompanied by complementary technological and organizational investments. Computerized provider order entry (CPOE) allows providers to interact with EMR data while making decisions in real time. Providers may use CPOE to view patient information, laboratory results, or notes from other providers. Furthermore, CPOE may be used when ordering prescriptions, tests, and radiological images.

Health IT systems vary in their functionality and use. Complementary applications may extend the effective reach of EMR and CPOE, facilitating communication across the disparate components of a care provider team. Two important applications are the electronic medication administration records (eMAR) and picture archiving communications systems (PACS). The eMAR helps close-the-loop in medication ordering and dispensing by connecting pharmacists, who fill prescriptions, to nurses, who administer prescriptions, at the patient's bedside.[8] Similarly, PACS facilitates communications with radiologists, potentially increasing the speed and quality of radiology consultations.

Health IT may improve clinical quality through a variety of mechanisms. These technologies may be used to automate routine, rules-based, clinical processes. Treatment guidelines or protocols may be embedded within health information systems. These protocols use patient-level EMR data to prompt providers with suggestions or raise flags regarding potentially risky interventions. These effects should be largest for patients facing common, standardized problems that conform to well-accepted care guidelines; furthermore, these effects should

[8]Many additional technologies are used with prescription pharmaceuticals such as electronic prescribing, designated pharmacy systems, automated dispensing, etc. We focus on EMR, CPOE, and eMAR as they are major investments and there was limited variation in the diffusion of these other technologies during our study period (e.g., automated dispensing remained rare while pharmacy management systems were widely diffused prior to our study period).

be critically dependent on the sophistication and use of health IT (Buntin et al., 2010; Jha et al., 2009). This form of direct clinical decision support is, arguably, the most emphasized mechanism in the health informatics and policy literature. Furthermore, the adoption and utilization of clinical decision support systems form the key requirements for federal subsidies under the 2009 HITECH Act.

Health IT may also effect quality in complicated cases that would not conform to standardized care guidelines. Many severely ill patients require extensive monitoring and testing. Health IT might improve information management and lead to improved treatment quality. Similarly, complex patients may require care from a wide range of clinical specialists that do not regularly coordinate care. Health IT may be particularly important for care coordination in complex patients.

These mechanisms are similar to those described in Autor et al. (2003). They find that IT substituted for labor involving rules-based tasks and complemented labor involving complex communications and decision making. Hospitals are an excellent environment for studying IT complementarities as the information content of tasks depends upon each patient's diagnoses. We build on this literature by exploring a rich set of technology adoption as well as patient-level diagnostic and treatment information.

2.1 Clinical Decision Support

Health IT may be used to provide direct clinical decision support. National provider organizations have developed treatment protocols for a wide range of common conditions with widely accepted standards of care. These rules-based protocols may be incorporated into a hospital's EMR and CPOE applications. The most common forms of decision support are treatment guideline automation and prescribing error checks.

Treatment guidelines recommend a set of care processes for patients with common diagnoses. Guidelines may recommend a series of tests and medications to improve diagnosis and treatment. Surgical patients, for example, are at high risk for both infections and blood clots (i.e., deep vein thrombosis). Problems that may be prevented through the administration of antibiotics and heparin respectively. Decision support systems could, for example, prompt physicians to prescribe these drugs for surgical patients. Decision support systems may also be used to prevent prescribing errors. Common errors include prescribing multiple drugs with adverse interactions, drugs for which patients have a known allergy, and drug dosing errors[9]. Decision support systems may automatically check for known drug-drug interactions or allergies recorded in a patient's EMR. While physicians may deviate from these protocols with good reason, automated decision support systems may prevent random errors which, according to the IOM (1999, 2001), are quite common.

Organizational and technological complements may be critical to achieving decision support effects. Decision support benefits from the adoption of EMR and CPOE along with the automation of care protocols. Furthermore, providers must enter orders electronically (e.g., electronic prescribing) to be influenced by these support systems. The benefits of these support systems are most likely to be realized by patients of moderate to low complexity. Standardized treatment guidelines are rarely implemented for complex combinations of diagnoses.[10]

Finally AMI serves as an interesting control condition. Similar to the other conditions we study, AMI is a common condition with widely accepted diagnostic and treatment protocols. However, these protocols are learned by rote, implemented rapidly, and the key tests and orders involve little interaction with information systems. Consequently, the effect of health IT on AMI outcomes should be lower than for other conditions. AMI patients may, however, benefit from a wide range of unobserved quality improvement initiatives (e.g, infection control, guideline implementation, etc.). In effect, AMI patients serve as a test for the validity of our identification strategy.

[9]Dosing errors are more common in children, but also occur in adult populations.

[10]Patients with numerous and severe comorbidities often require drug combinations that would not be used in typical patients.

2.2 Information Management and Care Coordination

Health IT may support clinical information management and care coordination. Many conditions require extensive monitoring and testing, generating large quantities of clinical information. Health IT may be used to capture and organize these data, thus expediting and improving treatment decisions. For example, renal failure affects a wide range of fluid and electrolyte levels. Providers must monitor and adjust these levels on an ongoing basis. For other conditions, monitoring of respiration and cardiac function may be crucial. Based on our discussion with physicians, we identified five conditions that require extensive information management. These include renal failure, diabetes, hypotension, sepsis, and hypoxia. Treatment for each of these conditions require monitoring of fluid, electrolyte, and/or oxygen levels. Furthermore, they involve a variety of lab tests. The monitoring process for each of these conditions generates a large volume of data that must be repeatedly evaluated by providers.

Health IT may also improve care coordination and communication. Many patients suffer from multiple conditions requiring treatment from a number of different clinical specialists. Most specialists treat a large number of patients in both inpatient and outpatient settings making regular communication costly. Physicians may also lack detailed knowledge of their colleagues' care plans. Health IT may reduce coordination and communication costs, providing physicians with easy access to their colleagues' treatment decisions.

We explore the roles of information management and coordination effects by allowing the impact of health IT adoption to differ based on the set patient diagnoses. Information management effects would lead to higher health IT benefits for patients with monitoring-intensive diagnoses. Similarly, care coordination effects would result in the benefits from health IT increasing in the number of clinical specialties. The construction of these measures is further described in the data and methods sections below.

3 Data

To perform our analyses, we combine detailed hospital IT adoption data with detailed hospital- and patient-level information from 2002-2007. Hospital IT data are drawn from the Healthcare Information and Management Systems Society (HIMSS) Analytics database and the 2007 American Hospital Association's Health IT Supplement. These data are combined with the American Hospital Association's (AHA's) annual survey, and the MEDPAR 100% inpatient Medicare claims data (2002-2007). Earlier years of these data sources, 1998-2001, are also used for some robustness tests. We also bring into the analysis the 5% Medicare Standard Analytic file of physician claims for 2007 and 2008.

The MEDPAR data provide detailed patient-level information for approximately 45 million aged Medicare beneficiaries with inpatient admissions. These data capture patient demographics, diagnosis and severity metrics, and outcomes. Patient-level severity and outcome measures are crucial for separating heterogeneity in clinical risk from the effects of health IT. Furthermore, these measures are important for discerning the mechanisms through which health IT effects outcomes. We employ three primary quality measures, sixty-day all-cause mortality, thirty-day readmissions (conditional upon survival) and length of stay. Other mortality and readmission durations are explored in robustness tests.

We focus on four high-frequency and high-severity diagnoses: acute myocardial infarction (AMI), congestive heart failure (CHF), coronary atherosclerosis (CA) and pneumonia. These conditions were selected because they are common, mortality is a common outcome and health IT can plausibly reduce medical errors and improve the quality of care. Models are estimated separately by primary diagnosis. As discussed above, health IT should, however, have a smaller effect on AMI patients.

CHF is a condition in which the heart can no longer pump enough blood to the rest of the body. It is the most common diagnoses for the Medicare population. Inpatient treatment can involve surgery or medical interventions. Coronary atherosclerosis is often treated by open heart surgery in which arteries or veins from elsewhere in the patient's body are grafted to the coronary arteries to bypass atherosclerotic narrowings and improve the blood supply to the coronary circulation supplying the myocardium. Patients generally spend 4 to 5 days recovering from the surgery in which the medical staff administer several different drugs and monitor the patient for fluid buildup and symptoms of pneumonia. Pneumonia is a lung infection where treatment requires prompt blood culture testing to determine the type of bacteria and the administration of the appropriate antibiotics. Acute myocardial infarction, commonly called a heart attack, results from the interruption of blood supply to a part of the heart, causing heart cells to die. AMI is leading cause of death in the US. Treatment can include drug therapy, percutaneous coronary interventions or coronary artery bypass grafts. Sample sizes range from 945,380 admissions for AMI to 2,476,543 for CHF.

The MEDPAR data do not contain significant detail on the identity of the physicians participating in the treatment during an inpatient stay. In order to construct our measure of the demand for care coordination described below we turn to the Medicare Standard Analytic 5% physician claims data. These data contain the claims submitted by physicians caring for patients during an inpatient episode. We use these data to identify the physician's primary speciality which is the critical input into calculating the expected number of unique clinical specialties participating in the treatment of each patient.

The HIMSS data include a rich set of information regarding hospitals' adoption and use of numerous HIT applications. We focus on two specific applications, CPOE and EMR, although we explore the role of other technologies such as eMAR and PACS. The HIMSS data describe each application's adoption date and whether it is in use rather than being installed.

The HIMSS Analytics data represent a large national panel of about 4,000 hospitals. With the exception of some small rural institutions, HIMSS Analytics forms a near census of acute care non-federal hospitals. This sample is remarkably stable across our study period. We matched more than 95% of hospitals from year-to-year across our sample. This suggests that our results are representative of most types of US hospitals; however, we exclude Critical Access, veterans, psychiatric and sub-acute hospitals.

Our data allow us to investigate a somewhat ancillary but important issue in health IT adoption: the role of network externalities from competitors' technology adoption. This exercise requires us to construct measures of neighboring hospital health IT adoption. Using the AHA latitude and longitude measures we construct distances between each hospital pair in our data. Hospital specific markets are defined as all other hospitals within a 20-mile radius of a given hospital. The number and proportion of neighboring hospitals with EMR and CPOE at $t-1$ are calculated for each hospital-specific market and is used as the primary right-hand side variable in the network externality analysis. While neighbors' EMR and CPOE adoption does not necessarily reflect an interoperable network it may well be correlated with the sharing of clinical data, the use of outpatient EMR systems, or skill spillovers in the provider labor market.

The AHA data complement the HIMSS data by describing hospitals characteristics. Important characteristics include: adjusted admissions, bed size, service scope, payer mix, multi-hospital system membership, and ownership status.

3.1 Meaningful Use Measures

The presence of health IT does not mean a hospital is using the technology in a meaningful way. In particular, guideline automation and electronic prescribing may be necessary to improve quality. In order to assess whether variation in IT utilization effects patient outcomes we construct meaningful use measures. To formulate this measure, we rely on the responses from 2007 AHA Annual Survey Information Technology Supplement. The HITECH Act (2009) contains provisions that will reward hospitals for the "meaningful use" of health IT. We construct our measure by mapping Stage I meaningful use criteria from the 2010 federal rule to the AHA IT supplement.

We construct and test six separate measures of Meaningful Use; however, we present two exemplar measures. The first examines the percent of 11 criteria that are fully implemented across all units and the second describes the percentage of medication orders written electronically. These criteria are drawn from three categories: electronic clinical documentation, computerized provider order entry for medications, and decision support.[11] The second

[11]Electronic clinical documentation criteria require that systems capture patient demographics, capture nursing assessment, keep problem lists, generate medication lists, and produce discharge summaries. Specific

measure is the percent of prescription orders entered electronically. Other measures are not reported but use more or less restrictive sets of criteria. These alternative measures yield results similar to the above Meaningful Use variables.

3.2 Measuring Clinical Information Management and Coordination

Health IT may be particularly valuable for managing complex clinical information. We identify five diagnoses that require extensive information management: renal failure, diabetes, hypotension, sepsis, and hypoxia. We denote these diagnoses IM conditions. These conditions require ongoing monitoring of fluid and electrolyte levels, frequent lab tests, and may require further monitoring of respiration or dialysis. Indicators for these conditions are based on the following ICD-9 codes: renal failure (584-586); diabetes (249-250); hypotension (458 and 796.3); sepsis including septicemia and bacteremia (038, 790.7, 995.91, and 995.92); and hypoxia (411.89, 799, and 997.01). Interviews with physicians further suggest that in the case of cardiovascular patients (i.e. patients with a primary diagnosis of CHF, CA, or AMI) the information management problems from sepsis are concentrated among patients also suffering from hypotension.

Health IT may facilitate care coordination across providers for a given patient. Care coordination difficulties are likely most acute when information needs to be shared across physicians who practice in different specialties. Using the Medicare Standard Analytic file, we select claims for inpatient treatment and calculate the distribution of physician specialties treating each diagnosis.[12]

Given these data, we construct an index of expected number of unique types of specialists that treat a patent with a given set of diagnoses. Let D_i denote the vector of patient i's diagnosis where D_i is an $n_i \times 1$ vector. Let the shares of specialist type g for diagnosis d be denoted by s_{gd}. This is simply the share of patients with an ICD-9 diagnosis code, d,

decision support criteria include: drug-drug interaction alerts, drug-allergy alerts, drug-dosing supports, clinical guidelines, and clinical reminders.

[12] For this exercise we link the physician inpatient claims to Medicare's data on physician specialty.

with a claim from a specialist of type g. For patient i, C_i is the expected number of unique specialists that will treat the patient and it is defined as:

$$C_i = \frac{1}{n_i} \sum_{d_i} \big(\sum_{g} s_{gd} \sum_{l \neq d} \sum_{g \neq k} s_{gl} \big). \tag{1}$$

In constructing C_i we are assuming that conditional on a given diagnoses, the distribution of specialist probabilities are independent across diagnoses. This is an important assumption and a limitation of this measure.

The structure of ICD-9 codes provides an additional measure of clinical scope. Diagnostic codes are organized by major classification of disease (MDC). We count the distinct MDC categories spanned by a patient's diagnoses as an additional measure of patient-level clinical coordination.

3.3 Severity Adjustment

Severity adjustment variables are used to control for patient-level heterogeneity and to explore the mechanisms through which health IT affects patient outcomes. Severity metrics are based on patients' demographics, admission type, current diagnoses, and treatment history. Demographic controls include age, gender, race, interactions between these groups and a third-order polynomial of age. Admission type indicators control for urgent, emergent, and transfer patients. Diagnostic measures include a weighted count of advanced diagnostic groups (ADGs) (Weiner, 1991), secondary diagnosis indicators (AMI, CHF, CA, PN, and diabetes), and indicators for the primary diagnosis subcategories. The primary diagnostic subcategories are based on fourth-digit ICD-9 codes except in the case of pneumonia where third-digit indicators were employed as it spans multiple 3-digit ICD9 codes. Finally, prior treatment controls capture whether a patient has been hospitalized in the past 6-months and the weighted ADG for the most recent admission within that period.

For some models we collapse all severity controls into a single linear index, s_{ijt} for patient i at hospital j at time t. This is accomplished by regressing outcome Y_{ijt} on observable patient characteristics, X^1_{ijt}, and a vector of time indicators τ_{1t}:

$$Y_{ijt} = \mu + X^1_{ijt}\lambda_1 + \tau_{1t} + \nu_{ijt}. \tag{2}$$

It is important to note that this equation does not include IT variables or hospital indicators as these variables would introduce endogeneity. Parameters are estimated by linear probability model[13] and then used to calculate a severity index, $s_{ijt} = E[Y_{ijt}|X_{ijt}, \hat{\mu}, \hat{\lambda_1}, \hat{\tau_{1t}}]$. In effect, s_{ijt} is simply the national average mortality rate for patients with observed characteristics, X_{ijt}, at time t.[14]

We also use severity to normalize our metrics of information management and clinical coordination. Mortality is regressed on a vector of information management indicators (M_{ijt}), the clinical coordination and MDC count indices (C_{ijt}), and other demographic and comorbidity controls (X^2_{ijt}),[15]

$$Y_{ijt} = \mu + X^2_{ijt}\lambda_{21} + C_{ijt}\lambda_{22} + M_{ijt}\lambda_{23} + \tau_{2t} + \nu_{ijt}. \tag{3}$$

Parameter from (3) are then used to construct severity-normalized coordination ($s^c_{ijt} = C_{ijt}\hat{\lambda}_{22}$), severity-normalized information management ($s^m_{ijt} = M_{ijt}\hat{\lambda}_{23}$), and other severity ($s^o_{ijt} = \hat{Y}_{ijt} - s^c_{ijt} - s^m_{ijt}$). Since C_{ijt} and M_{ijt} do not capture all diagnoses requiring clinical coordination and information management, our empirical models will be biased against finding information and coordination effects from health IT.

[13]We have confirmed that results are quite similar when using probits but focus on LPM for computational tractability when boot-strapping standard errors.

[14]The severity measure and subsequent model results are nearly identical if parameters are allowed to vary across time.

[15]Note that the current weighted ADG score and the secondary diagnosis indicators (PN, CHF, CA, AMI) are excluded from X^2_{ijt} because of partial multicollinearity (e.g., the ADG score is based, in part, on our information management indicators) and their conceptually ambiguous relationship to information management and clinical coordination.

4 Empirical Strategy

Our empirical strategy is straightforward. We estimate the impact of hospital health IT adoption on patient outcomes for patients with different sets of diagnoses and severities of illness. When the outcomes are discrete, we estimate the parameters using linear probabilities models with hospital fixed effects including a very rich set of patient demographics and seventy of illness controls.[16] The hospital fixed effects control for time invariant differences in hospital quality of care that may be correlated with IT adoption. That is, we use a difference-in-difference identification strategy relying on variation in the timing of adoption to pin down the parameters of interest. As we document below, there is significant variation in the timing of adoption of health IT across hospitals.

If hospitals experience time-varying quality shocks that are correlated with IT adoption, then our estimates will be biased. We employ a number of robustness checks to test the likelihood that correlated, time varying shocks are present. To summarize, we find little evidence to suggest that hospitals that adopt health IT (or do so earlier) have differential quality (either time invariant or time varying) than non- or late adopters. We also test the robustness of our findings to different definitions of health IT adoption and its utilization.

Much of the focus of this paper is devoted to estimating heterogeneous health IT effects in order to uncover the mechanisms through which IT affects outcomes. We estimate those effects within the linear probability models discussed above by including interactions between different patient severity measures and health IT adoption. We test the robustness of these models by allowing the heterogeneity to enter flexibly. Below we provide more detail on specific models.

Base Model: We model the latent health state for patient i at time t within hospital j, M^*_{ijt}, as a function of patient characteristics and hospital factors. Higher values of M^*_{ijt} correspond to poorer health. For two out of three outcomes and for the outcome that is our central focus, we do not observe M^*_{ijt}. When the outcome of interest is discrete (e.g. 60-day mortality), $M_{ijt} = 1$ if $M^*_{ijt} > 0$ and 0 otherwise. If the outcome is approximately continuous

[16] We also estimated the models using probits and the results we essentially identical but we had difficulty computing standard errors for marginal effects in the nonlinear specifications.

(i.e. length of stay) then $M_{ijt} = M^*_{ijt}$. Patient characteristics include demographic and severity measures (X_{ijt}) from (2) above.

The focus here is on the impact of the impact of health IT on health. We begin by defining T_{jt-1} as an indicator equal to one if a hospital has both EMR and CPOE at time $t-1$. This definition is a simplification and implicitly assumes that the adoption of these two applications represents a substantial increase in a hospital's health IT. Furthermore, the lag $(t-1)$ implies that the benefits of health IT follow adoption by 1-year - these assumptions are tested in subsequent analysis.

Our base empirical specification is:

$$M^*_{ijt} = \alpha_j + X_{ijt}\beta_1 + T_{jt-1}\gamma_1 + \tau_t + \epsilon_{ijt}, \tag{4}$$

where α_j is a time invariant hospital-specific outcome effect that may be correlated with the other right-hand side variables. In this framework, γ_1 measures the average change in the patient's health state resulting from health IT adoption. The terms β_1 and τ_t are other parameters to be estimated, τ_t is a set of time indicators and ϵ_{ijt} is an error term.[17] We estimate a linear probability model using the usual linear fixed effects transformation.[18] Equation 4 is estimated separately for patients with a primary diagnosis of AMI, CHF, CA, and PN. These equations are estimated using three different outcome measures, mortality within 60-days of admission, readmission within 30-days of discharge, and length of stay.

Technological and Organizational Complementarities: Hospitals exhibit variation in both the capability and utilization of their EHR systems. The returns to health IT may depend on complementary technological and organizational investments. In particular, rules-based decision support systems require a sophisticated set of IT applications, automated treatment guidelines, and the use of electronic prescribing. We estimate a series of models to test whether complementary organizational inputs affect the effectiveness of health IT.

[17] While we do not index the error terms by equation, the error terms in each equation are unique to the equation.

[18] Errors are clustered by hospital to address correlation across patients within the hospital and for the same hospital across time. The errors also are heteroskedasticity robust.

Finally, using this basic framework we test for the potential role of cross-hospital spillovers or network effects in health IT adoption by including neighboring hospitals' adoption of IT as a regressor.

We utilize data from the 2007 AHA EMR supplement to measure complementary organizational inputs. We denote organizational inputs by O_j and estimate parameters from the following equation:

$$M^*_{ijt} = \alpha_j + X_{ijt}\beta_3 + T_{jt-1}\gamma_3 + O_j T_{jt-1}\delta_3 + \tau_t + \epsilon_{ijt}. \tag{5}$$

The parameters in Equation 5 are estimated using two alternative utilization measures, the first describes the percent of 11 key capabilities used to support decision support algorithms while the second describes the percent of pharmacy orders entered electronically. For the sake of brevity, in these and the rest of the models in the paper, mortality is the primary outcome variable.

Severity, Information Management, and Coordination: The benefits from health IT adoption may be heterogeneous across both patients and hospitals. Health IT's data collection capabilities might better capture and reduce the cost of communicating clinical information, and this information may be particularly useful for treating complex, high-severity patients. For ease of interpretation, we collapse our demographic and severity adjustment variables into a single index, s_{ijt}, described in Equation 2. We then measure the effect of health IT allowing information effects to depend on patient severity:

$$M^*_{ijt} = \alpha_j + X_{ijt}\beta_4 + s_{ijt}\gamma_4 + T_{jt-1}\delta_4 + f(s_{ijt}, T_{jt-1}) + \tau_t + \epsilon_{ijt}, \tag{6}$$

where γ_4, δ_4, and the function f capture the effect of IT on the patient's health state and how it varies with patient severity. The function f is estimated using both simple (linear) parametric and a flexible four knot cubic spline methods.

As discussed above, health IT can facilitate nurses' and physicians' abilities to manage, process and ultimately act upon the large amounts of information the care of complex, severely ill patients requires. Health IT also may reduce the cost of communicating information across different actors in the patient care process. Most Medicare patients are admitted with multiple diagnoses. Different conditions require differing amounts of information processing and care coordination. As discussed in Section 3, using Equation (3) this variation allows us to decompose patient severity into components that require information management (s^m_{ijt}), care coordination (s^c_{ijt}), and other factors (s^o_{ijt}). We then estimate the parameters from the following equation to better understand the underlying mechanisms through which IT affects patient health,

$$M^*_{ijt} = \alpha_j + X_{ijt}\beta_5 + s_{ijt}\gamma_5 + T_{jt-1}\delta_5 + s^m_{ijt}T_{jt-1}\delta_{51} + s^c_{ijt}T_{jt-1}\delta_{52} + s^o_{ijt}T_{jt-1}\delta_{53} + \tau_t + \epsilon_{ijt}. \quad (7)$$

The parameters δ_{51}, δ_{52} and δ_{53} capture the impact of health IT adoption on the management of patient information, care coordination and all other components of severity, respectively. The variables s_{ijt}, s^m_{ijt}, s^c_{ijt}, and s^o_{ijt} in Equations (6) and (7) are all estimated thus we need to adjust the standard errors to account for this. We block bootstrap the standard errors reestimating Equations (4) and (5) and recalculating the different s_{ijt}'s in each iteration.

Learning and Innovation: Information technology and its value may evolve over time as IT manufacturers leverage improvements in computing power and reductions in the cost of data storage and invest in improving the functionality and ease of use of their systems. If innovation in these technologies is meaningful, the patient benefits from IT may improve over time. Conversely, learning might increase the effective value of older information systems. We explore vintage affects of health IT adoption by letting the value of IT depend on the year of adoption. This provides a simple test of learning and innovation effects.

5 Adoption Patterns and Summary Statistics

Figure 1 graphs the cumulative adoption rates of different health IT systems from 1998 to 2007. Recall that our patient level data span 2002 to 2007. At the beginning of our data only 16% of hospitals had installed an EMR and 1% of hospitals had acquired a CPOE system.

eMAR system were almost never present in 2002. By the end of the sample, approximately 33% of hospitals had adopted an EMR, 28% had installed an eMAR and 17% had acquired a CPOE system.

Basic patient-level summary statistics by primary diagnoses are presented in Table 1. Not surprisingly, the sample is predominately white and elderly with the mean age between 75 and 80 years old, depending on the primary diagnoses. The average patient in our sample are quite ill, and this can been seen in several of the variables. Across the diagnoses, the weighted ADGs are between 4.5 and 6.2. The average number of unique MDCs is over three for all primary diagnoses and the average number of expected, unique specialists that these patients see given their set of diagnoses is over three for all conditions. While the typical patient is quite ill there are large variations in the severity of illness across patients for all our primary diagnoses. Across the diagnoses, the coefficient of variation ranges between .38 and .30.

Given that the average patient patient in our sample is very sick, it not surprising that the outcomes for three of the four primary diagnoses are poor. Ignoring CA, 60-day mortality rates range from 16% for pneumonia and CHF to 24% for AMI. The mortality rate for CA is a much more modest 3.6%. The typical length of stay is between 4.5 and 6 days with large variations across patients in the amount of time they spend in the hospital. Readmission is common. Twenty-two percent of CHF patients are readmitted within 30 days while 15% of pneumonia patents are readmitted in 30-days. Readmission rates for AMI and CA fall in between those extremes.

Tables 2 and 3 present mean patient and hospital characteristics by hospitals' final IT adoption status. Patient characteristics of adopters and non-adopters are very similar with few exceptions. That is, there is little evidence that patents are sorting to adopting and non-adopting hospitals based on observable severity measures. Interestingly, there is virtually no difference in mean mortality, readmission or length of stay between adopters and non-adopters. However, hospitals that adopt health IT are notably different than non-adopters. Adopters are, on average, slightly larger, more likely to be nonprofit institutions and less likely to be a member of a multi-hospital system. As we include hospital fixed effects in the estimation, the validity of our approach will turn on whether shocks to hospital outcomes are correlated with the adoption of health IT. As discussed above with the results presented below, we do not find evidence suggesting that this is the case.

6 Results

6.1 Base Model of Health IT and Health Outcomes

Equation 4 results are reported in Table 4. We find no effect of health IT adoption on either mortality or length of stay although we do observe a very small increase in length of stay for CHF and a small reduction in readmissions for CA. In only two of the 12 regressions is the coefficient of interest significantly different from zero and in those cases it is small in magnitude. It is important to note that the statistical insignificance does not reflect imprecise estimates; rather, we have precisely measured parameters that are extremely close to zero. The 95% confidence interval does not include a 1% mortality reduction for most diagnosis. In the Appendix we present results from a simple OLS model without fixed effects but include hospital characteristics to the set of independent variables. Interestingly, results from this specification are essentially identical to those in Table 4 suggesting that hospital health IT adoption is not correlated with time-invariant hospital unobservables.

The results in Table 4 are noteworthy. They provide strong evidence that the average treatment effect of health IT is near zero. While consistent with McCullough et al. (2010) and Agha (2011) these findings differ from much of the health informatics and medical literatures (Buntin et al., 2011).[19] Taken by themselves, these findings suggest that there is no there there for health IT and that policies designed to increase the diffusion of health IT will have little impact on patient outcomes. However, as we show below, the actual impact of health IT adoption on patient outcomes is more subtle. We attribute the differences in our results from the broad informatics literature to our study design. We analyze the outcomes for all FFS Medicare inpatient admissions (subject to the exclusion criteria described in the Data

[19]These results are not sensitive to other patient outcome measures. McCullough et al. (2010) uses patient safety indicators as the dependent variable and finds similar results.

section) and control for time invariant differences in hospital quality performance. The vast majority of the studies in the informatics literature are single (or few) sites studies relying on a pre/post design and with few exceptions the literature does not address the potential endogeneity of health IT adoption.

The results presented in Table 4 are robust to alternative measures of health IT. We estimate the parameters of Equation 4 using both more and less restrictive definitions of health IT adoption. Parameter estimates from alternative definitions do not change the basic conclusion. In Panel A of Table 5 we present results from one alternative model defining health IT adoption has having installed four major IT components: EMR, CPOE, eMAR and PACS. As in Table 4, parameter estimates are all small and insignificantly different from zero implying that our null results is not a consequence of our specific definition of health IT adoption.

Technological and Organizational Complementarities: One concern is that our null finding could be biased as our specifications fail to account for the role of unobserved technological and organizational inputs. In particular, Equation 4 does not measure the inputs required to implement rules-based decision support capabilities. Beyond addressing a potential omitted variables issue, understanding the role of organizational heterogeneity in the use of technology on its effectiveness is a longstanding question we can examine. To investigate this possibility, we estimate the parameters in Equation (5) using a variety of alternative organizational and technological input measures.

Table 5 Panel B allows the effect of health IT adoption to depend on an index of meaningful use criteria. This index captures the use of automated treatment guidelines and related technological inputs. Similarly, the results reported in Panel C allow the benefits to depend on physicians' actual use of electronic prescribing (i.e., the percent of pharmacy orders made electronically). We find no evidence that the effect of health IT depend upon complementary organizational and technological inputs. This null result was robust to alternative patient outcome measures as well as a wide range of alternative specifications and meaningful use metrics.

Health IT value could also depend upon the local IT infrastructure. That is, there could be spillovers from network externalities or IT labor agglomeration economies. Ideally, patients' clinical histories would be available in an interoperable electronic health record system. While such systems remain quite rare, neighboring providers' health IT adoption may generate spillovers through PACS systems, electronic lab result communication, or even providers' acceptance of and skill in health IT utilization. We allow the effect of health IT to depend on neighboring hospitals' health IT adoption. Table 5 shows that EMR & CPOE are not more effective when the percent of neighboring hospitals with EMR & CPOE increase. We obtain the same result for the number of neighboring hospitals, using more flexible functions of neighboring hospitals' adoption, or using alternative outcome measures.

Severity, Information Management and Coordination: We next explore potential heterogeneity in the impact of health IT as a function of patient seventy by estimating the parameters from Equation (6). We estimate f, the function that relates severity and health IT adoption to mortality, using two different approaches. The first parameterization is a simple interaction between T_{jt-1} and s_{ijt}. Panel A in Table 6 presents the results from this specification. We find that health IT has a significant effect on mortality but that the effect is small (or even positive) for low-severity patients and that the benefits from IT adoption increase with severity. While the parameters are difficult to interpret directly, the marginal effects at the mean severity are -0.5% for PN, -0.01% for CHF, -0.01% for CA, and -0.0001% for AMI. However, this linear functional specification for f is rather restrictive. Our next model allows severity and its interaction with health IT to follow a more flexible specification. We employ a four-knot cubic spline of severity and interact this function with health IT adoption in the linear probability model.[20]

Table 6, Panel B presents parameter estimates from this spline specification. While the parameter estimates are difficult to interpret directly, Figure 2 graphs the marginal effects of health IT and their 95% confidence intervals by decile of severity implied by this spline specification. While health IT has no measurable benefit for relatively healthy patients, it

[20]We employed a variety of specifications and found found that they yielded similar results to those described in Figure 2, below. Knots were placed equally across the marginal distribution of s, see Harrell (2001) for further details.

significantly decreases mortality for relatively high-risk PN, CHF, and CA patients.[21] Adoption decreases mortality in the 60^{th} decile of severity and higher and significantly decreases mortality among CHF and CA patients in the highest severity decile. Qualitative work suggests that the relatively large PN effect may be due to the increased role of medical (as opposed to surgical) treatment and the important role played by lab result monitoring and nutrition coordination for high-risk patients. The AMI estimates are an order of magnitude lower than those for other conditions and not statistically significant at any severity level.

Integrating the IT adoption effects over the severity distributions corresponds to averting 0.83 deaths per hospital per year. While the average effect is modest, adoption at hospitals with large and complex patient populations avert as many as 8 deaths per year. The benefits are most notable for pneumonia and CHF, where health IT adoption reduces 60-day mortality by 0.67 and 0.12 deaths per hospital per year respectively. These diagnoses are frequent, high-risk, and sensitive to health IT adoption. Adoption has a smaller effect on CA patients, averting 0.04 deaths per hospital per year, as this diagnosis has a much lower average mortality rate. The point estimates imply that health IT adoption has almost no effect on aggregate AMI mortality (-0.0006).

The estimated mortality reduction aligns with the results in Miller and Tucker (2011). They find that EMR adoption reduces infant mortality by approximately 13 deaths per 100,000 births. We are examining the impact of health IT on the opposite end of the life cycle spectrum with a patient population that is more severely ill with a much higher baseline mortality rate. Thus our estimates should differ in magnitude from Miller and Tucker (2011).[22] Across the conditions we study, we find an average mortality reduction of approximately 200 deaths per 100,000 admissions from IT adoption. The impact is largest for PN where IT adoption is estimated to prevent 500 deaths per 100,000 admissions while IT adop-

[21] It is important to note that in nearly all specifications we find that health IT adoption is associated with a small decrease in quality for low-risk patients. These effects are always small and usually statistically insignificant. They may, however, reflect difficulties that may arise from using EMR & CPOE systems with imperfect interface design. The effort required to use such systems could degrade average quality while the benefits from information management and care coordination would only accrue to higher-risk patients.

[22] Our IT sensitive measures have an average 60-day mortality rate of 15% while child birth has an average 7-day mortality rate of 0.5%.

tion reduces approximately 10 deaths per 100,000 admissions for both CA and CHF. Health IT's effect on AMI mortality is approximately zero.

One concern is that health IT adoption could be correlated with other organizational and health care process change in the hospital and that our estimates are reflective of these changes and not capturing the real health IT impact of adoption. Recall that AMI is our control condition. Our priors are that health IT should not affect health for those patients. The lack of an effect for AMI patients suggests that our estimates are capturing true health IT adoption effects rather than unobserved quality improvement initiatives that may be correlated with IT investments.

We dive deeper into the data in order to understand the mechanisms behind IT's heterogeneous treatment effects. To do this we estimate the relationship between health IT and the presence of complex, clinical information and the requirements to coordinate patient care across specialists. We do this by estimating the parameters from Equation (7). Table 7 reports results for this model for the four separate primary diagnoses. As expected, each of the component severity metrics has a parameter of approximately 1. The parameter estimates of the health IT interactions with the different components of severity, with one exception, are all negative.

The parameters for s^c_{ijt} and s^m_{ijt} are most precisely estimated for PN patients. Here health IT facilitate both care coordination and information management. An increase in expected mortality associated with care coordination is reduced by 8.8% and an increase in mortality associated with information management is reduced by 11% for PN if the hospital has adopted Health IT. Health IT has a significant effect for CHF patients with care coordination problems. For CA patients, IT has its largest impact on patients with conditions requiring greater information management. While health IT does not affect mortality for the average patient, it has striking benefits for patients whose diagnoses span other clinical specialties; essentially, health IT does not affect outcomes for the typical AMI patient, but when they do realize mortality reductions when their secondary diagnoses require coordination with other clinical specialties.

For three of the four primary diagnoses, the sum of the coefficients on the health IT interactions for care coordination and information management are notably larger than the coefficient on the interaction with other factors that drive severity. That is, the estimates point to health IT affecting high-severity patients by facilitating cross-provider communication and helping hospital staff manage clinical information. The roles that IT plays in these task appears to vary across primary diagnoses. Finally, these estimates likely understate information and coordination effects as s^o certainly includes some variation based on information management and care coordination problems.

These results emphasize the importance of task-level complementarities between IT and and labor inputs (Autor et al., 2003; Hubbard, 2003; Baker and Hubbard, 2003; Acemoglu and Autor, 2011). In particular, Autor et al. (2003) argue that IT facilitates complex coordination and problem solving tasks when used in high-skill settings. Our findings demonstrate that within firms the benefits from IT depend on the information content of tasks, especially the need for labor coordination and information management. Despite the emphasis of the health informatics and health policy literatures, we find little support for the hypothesis that health IT improves quality through rules-based decision support. This may be due to the tremendous complexity of medical decision making. Clinical decisions should be especially difficult to automate. While our results do not emphasize the role of complementary organizational inputs, other studies suggest that these issues are relevant to health IT utilization and value (McCullough and Snir, 2010; Dranove et al., 2012).

Learning and Innovation: Results from a sample test model are reported in Table 8.[23] We find no evidence that IT value changes significantly over time. While innovation and learning certainly matter, the relatively small magnitude is unsurprising. The wider IT and productivity literature finds IT value grows slowly and is difficult to detect empirically (Brynjolfsson and Hitt, 2003; Stiroh, 2002). Lee et al. (2012) find that hospital IT investments productivity effects mirror other industries and are stable over time. Furthermore, time motion studies of health IT value often find learning effects, but these effects occur in less than 1 year.

[23] Although not reported here, we explore a series of related tests for identifying learning and innovation effects. To date, all tests suggest that these effects are too small to be detected.

6.2 Robustness

Our ability to estimate causal relationships between IT adoption and health outcomes is dependent upon the validity of our difference-in-differences identification strategy. For this strategy to be valid, unobserved changes in hospital quality must be uncorrelated with the adoption of health IT. Clearly, there are plausible threats to this identification strategy. Hospitals could, for example, adopt IT in response to identified quality problems. Hospitals might also simultaneously invest in other, unobserved, quality-improvement initiatives. Finally health IT could change the distribution of patient severity.

We construct a series of tests for these potential threats to identification. If health IT were adopted in response to quality problems then leads of health IT adoption (e.g., health IT adoption at $t+1$ and $t+2$) would appear to decrease quality. We estimate models with indicators for the two periods preceding IT adoption. These results are reported in Table 8 Panel C. We find that future adoption is uncorrelated with current quality while lagged IT adoption continues to improve quality for high-risk patients. We also estimated this model interacting the technology adoption lead indicators with patient severity. The adoption lead effects continued to be small and insignificant although lagged IT effects were no longer statistically significant.

The AMI effect provides an additional identification test. AMI involves less medical management and fewer medical record (paper or electronic) interactions during the initial and critical steps of treatment. Health IT should have a smaller effect on AMI although it may be sensitive to other quality improvement initiatives. Health IT effects are between 5- and 20-times larger for CHF, CA, and PN than for AMI (see Table 6). We also estimate Equations 4-6 using patient safety indicators (PSIs) that should not be sensitive to health IT. Health IT should not affect the rate of accidental punctures, foreign bodies left during procedures, or postoperative hip fractures.[24] Health IT has no effect on these non-sensitive quality metrics.

We also considered the possibility that health IT adoption could effect the distribution of

[24]See the technical appendix to Parente and McCullough (2009) for further discussion of these tests.

patient severity. Health IT could alter severity measurement through coding changes and it could effect physician and patient preferences across hospitals. We found that patient severity was uncorrelated with IT adoption. We also estimated our models separately for elective and emergent admissions as emergent admissions as selection based on severity should be more prevalent for elective admissions. We found similar results across these different admissions types.

We explore many alternatives specifications for Equations 4 - 7.[25] Time trends, captured by τ_t could be heterogeneous. While models with hospital-specific time trends did not converge we achieved similar results by allowing time trends to differ across groups of hospitals (e.g., those who ever adopted and those who never adopted). Correlation between controls (X_{ijt}) and the construction of s_{ijt} could bias the standard errors of the marginal effects of T_{t-1}. Alternative specifications replacing X_{ijt} with flexible functions of s_{ijt} yielded similar results. Ultimately, the finding that health IT improves outcomes for high-severity patients is remarkably consistent across all the specifications we estimated. We also explored the implications of our assumed linear probability model. We confirmed our results using probits and logits.[26]

7 Conclusion

We measure the effect of health IT on inpatient clinical outcomes using a difference-in-differences identification strategy and detailed patient-level data. While we find no relationship between IT and quality for the average patient, IT does improve outcomes for patients with complex, high-severity, diagnoses. The total effect is modest. Health IT adoption averts

[25] We have estimated many specifications reflecting a variety of alternative hypotheses as well as robustness tests and repeated tests of the same hypotheses. The large number of regressions does create the potential for spurious correlation on occasion to appear significant. We believe this is unlikely given the consistency of results within hypotheses. However, we employed a retention sample to guard against this possibility. We first estimated Equations 4-6 for a wide range of specifications using a 20% subsample. We then then confirmed these findings with a separate 20% subsample and then the full sample. Results were similar across samples in each case.

[26] We note however that the standard errors for the marginal effects of T_{t-1} did not converge when using the delta method in some non-linear specifications.

200 deaths per 100,000 admissions across the IT sensitive conditions we examine.[27] We find no relationship between health IT and either readmissions or length of stay.

The health IT policy literature and the first-stage Meaningful Use rules emphasize the role of clinical decision support systems. These systems implement rules-based algorithms to prevent and correct clinical errors. Our results do not suggest that health IT improves quality through rules-based decision support systems. Rather, we find that health IT improves quality by facilitating coordination and communication across providers and by helping providers manage clinical information. These mechanisms lead to relatively high benefits among high-risk patients. These mechanisms are often overlooked in the health IT debate but play an important role in the broader IT and economics literature (Autor et al., 2003; Acemoglu and Autor, 2011).

These findings may also offer an explanation regarding why economic studies of health IT and health outcomes (McCullough et al., 2010; Agha, 2011; Miller and Tucker, 2011) are often less optimistic than studies in the clinical and informatics literature (Hillestad et al., 2005; Buntin et al., 2011). Most studies of health IT value are performed at large academic medical centers - institutions that specialize in complex cases. The effect of health IT on quality should be higher at these institutions. These findings further suggest that the high returns from academic institutions should be difficult to duplicate at the average US hospital even with the adoption and utilization of sophisticated decision support systems.

An important limitation of our study is that our data do not include the effects of newer, potentially better, information systems. However, our results suggest a slow rate of effective innovation for health IT. More recent technologies are correlated with larger mortality reductions, but these effects are quite small and not statistically significant. This apparently slow productivity growth rate is similarly to the evolution of average IT value in other industries (Stiroh, 2002; Brynjolfsson and Hitt, 2003) and of health IT on general productivity (Lee et al., 2012). Similarly, learning effects and cross-hospital adoption spillovers appear to have little effect on the health IT and quality relationship.

[27] These numbers only reflect the FFS Medicare population diagnosed with pneumonia, CHF, CA, and AMI, total mortality reductions would be larger.

While we include measures of health IT utilization our results should not be interpreted as measuring the consequences of Meaningful Use from the HITECH Act. Rather, we employ cross-sectional Meaningful Use data to provide evidence that our estimates are robust to health IT measurement error. The value of Meaningful Use merits further study.

A further limitation is that our data do not capture all of health IT's potential benefits. Information technology might enhance quality of care and the patient experience without effecting mortality, readmissions, or length of stay. We have, however, found similar results when studying patient safety indicators. Other studies using panel data techniques have found only small changes in process quality measures (McCullough et al., 2010; Jones et al., 2010) following health IT adoption. Health IT may also effect the efficiency of health care delivery systems (Borzekowski, 2010; Lee et al., 2012; Agha, 2011; Dranove et al., 2012). Ultimately, our estimates likely underestimate the welfare effects from health IT adoption and largely ignore potential cost reducing benefits.

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8 Figures and Tables

Figure 1: Diffusion of health IT applications

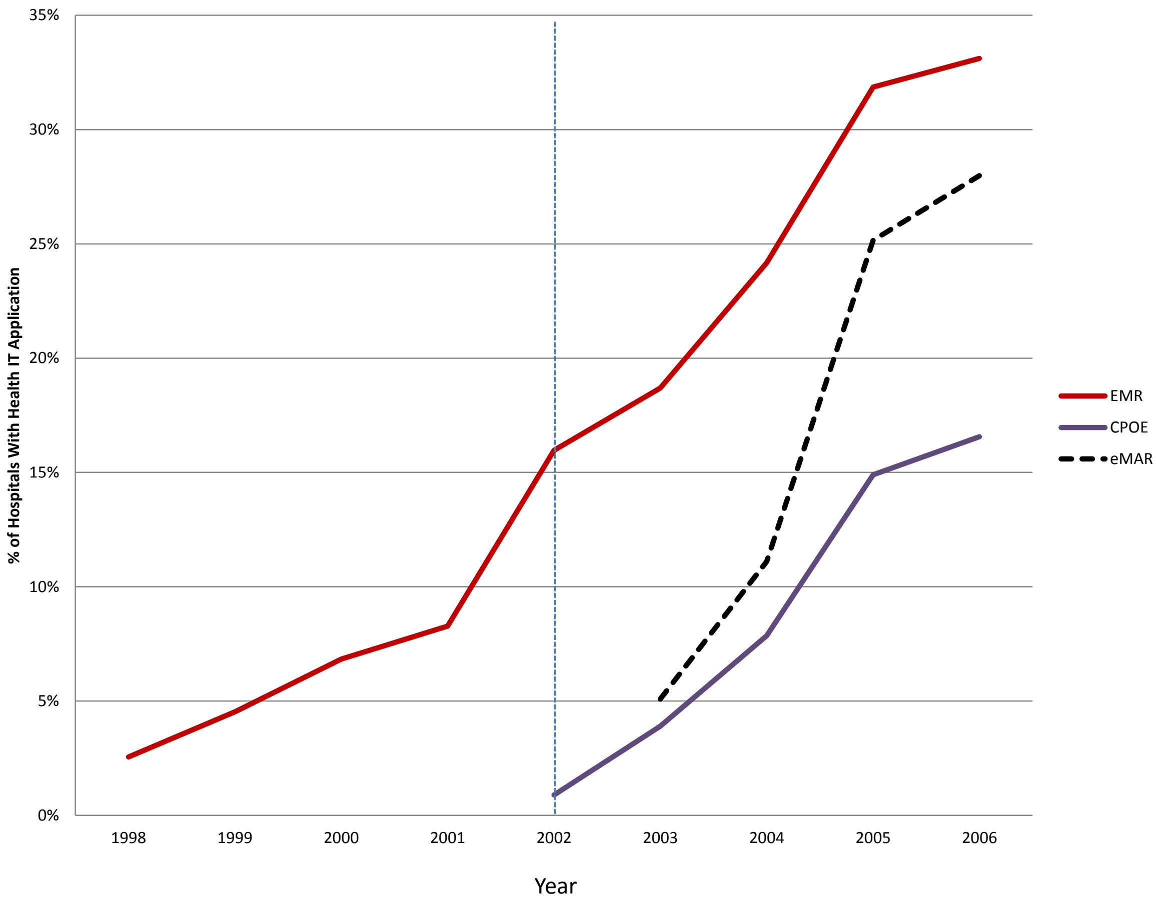

Figure 2: Marginal effect of health IT on mortality by diagnosis and deciles of severity

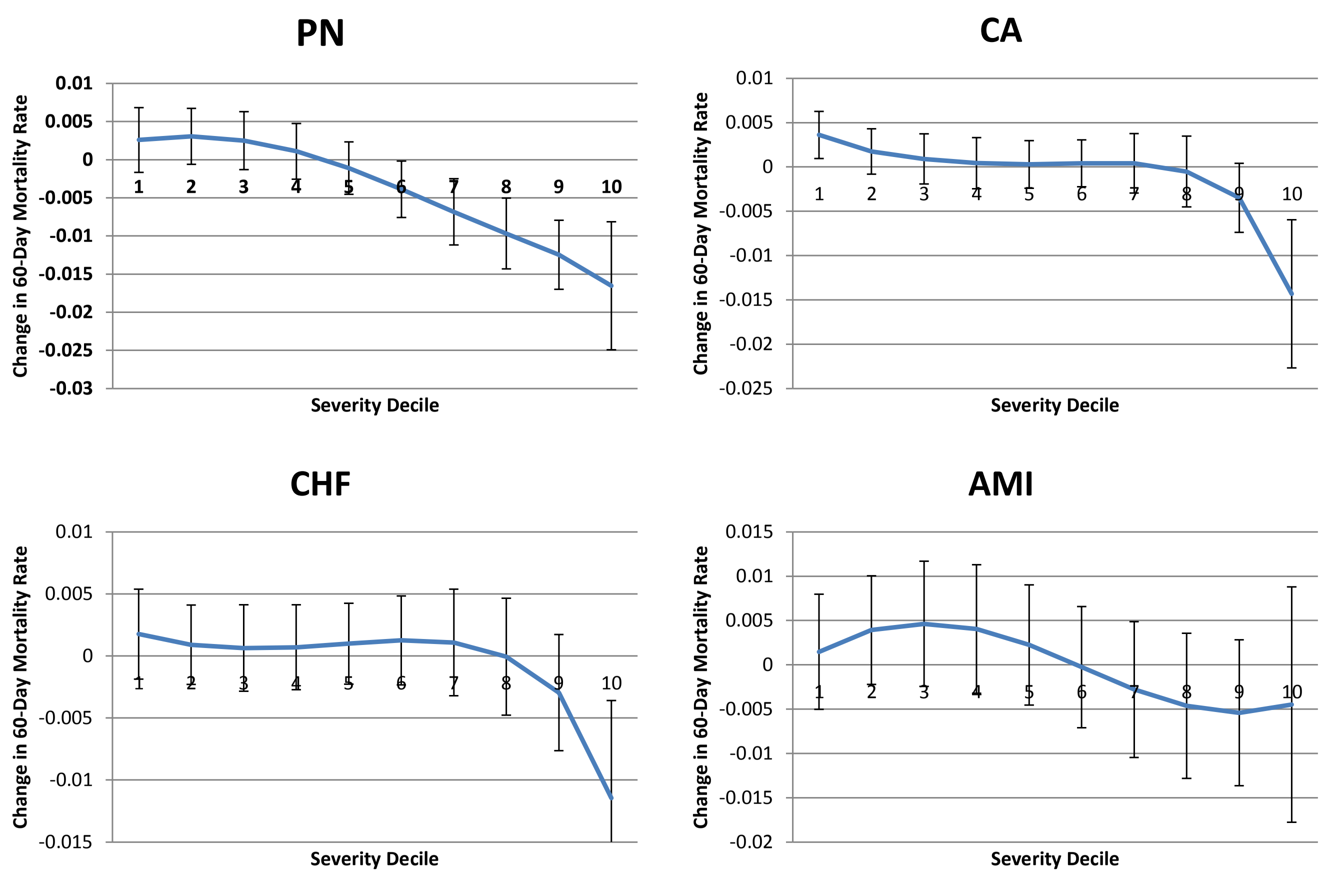

Table 1: Means and (standard deviations) of patient characteristics by primary diagnosis

Variable	PN	CHF	CA	AMI
Admissions	2,167,654	2,399,648	1,004,402	914,317
Female	0.551	0.568	0.452	0.524
	(0.497)	(0.495)	(0.498)	(0.499)
White	0.878	0.830	0.870	0.872
	(0.327)	(0.375)	(0.336)	(0.334)
Age	80.00	79.99	75.77	79.59
	(8.402)	(8.412)	(7.078)	(8.437)
Weighted ADGs	6.16	5.22	4.54	4.90
	(1.858)	(1.647)	(1.565)	(1.859)
Emergent	0.704	0.703	0.492	0.720
	(0.456)	(0.457)	(0.5)	(0.449)
Urgent	0.219	0.214	0.242	0.218
	(0.414)	(0.41)	(0.428)	(0.413)
Transfer	0.034	0.035	0.085	0.121
	(0.181)	(0.183)	(0.279)	(0.326)
Specialists, C_i	3.59	3.58	3.34	3.56
	(0.816)	(0.76)	(0.834)	(0.783)
Number of MDCs	4.25	3.63	3.09	3.48
	(1.281)	(1.234)	(1.161)	(1.228)
Number of IM Diagnoses	0.512	0.649	0.431	0.569
	(0.76)	(0.766)	(0.592)	(0.718)
Length of Stay	5.85	5.39	4.46	5.94
	(4.452)	(4.576)	(4.676)	(5.506)
Readmission, 30-day	0.150	0.221	0.166	0.209
	(0.358)	(0.415)	(0.372)	(0.407)
Mortality, 60-day	0.157	0.161	0.036	0.240
	(0.364)	(0.367)	(0.185)	(0.427)
Severity, coordination (s^c)	0.109	0.123	0.032	0.145
	(0.033)	(0.038)	(0.012)	(0.045)
Severity, information mgmt. (s^m)	0.010	0.006	0.006	0.031
	(0.034)	(0.052)	(0.025)	(0.070)
Severity, other (s^o)	0.038	0.032	0.002	0.064
	(0.063)	(0.055)	(0.018)	(0.102)

From MEDPAR data

Table 2: Means and (standard deviations) of patient data by primary diagnosis and final hospital IT adoption status

	PN		CHF		CA		AMI	
Variable	non-Adopters	Adopters	non-Adopters	Adopters	non-Adopters	Adopters	non-Adopters	Adopters
Admissions	1,942,619	225,035	2,134,909	264,739	88,4516	119,886	804,376	10,9941
Female	0.551	0.546	0.569	0.563	0.455	0.432	0.524	0.520
	(0.497)	(0.498)	(0.495)	(0.496)	(0.498)	(0.495)	(0.499)	(0.5)
White	0.881	0.855	0.834	0.803	0.872	0.856	0.874	0.853
	(0.324)	(0.353)	(0.372)	(0.398)	(0.334)	(0.351)	(0.332)	(0.354)
Age	80.00	80.04	80.01	79.83	75.80	75.55	79.62	79.36
	(8.391)	(8.492)	(8.404)	(8.477)	(7.09)	(6.983)	(8.439)	(8.42)
Weighted ADGs	6.16	6.17	5.22	5.24	4.54	4.52	4.89	4.91
	(1.856)	(1.871)	(1.646)	(1.658)	(1.564)	(1.573)	(1.859)	(1.861)
Emergent	0.700	0.745	0.699	0.733	0.493	0.483	0.721	0.718
	(0.458)	(0.436)	(0.459)	(0.443)	(0.5)	(0.5)	(0.449)	(0.45)
Urgent	0.223	0.193	0.217	0.194	0.243	0.238	0.216	0.228
	(0.416)	(0.394)	(0.412)	(0.396)	(0.429)	(0.426)	(0.412)	(0.42)
Transfer	0.034	0.037	0.033	0.047	0.080	0.126	0.112	0.187
	(0.18)	(0.189)	(0.18)	(0.211)	(0.271)	(0.331)	(0.315)	(0.39)
Number of Specialists, C_i	3.59	3.59	3.58	3.58	3.35	3.34	3.56	3.58
	(0.816)	(0.817)	(0.761)	(0.753)	(0.835)	(0.827)	(0.786)	(0.759)
Number of MDCs	4.25	4.26	3.64	3.60	3.09	3.06	3.48	3.46
	(1.282)	(1.277)	(1.235)	(1.226)	(1.163)	(1.145)	(1.23)	(1.213)
Number of IM Diagnoses	0.512	0.515	0.648	0.653	0.430	0.441	0.569	0.569
	(0.76)	(0.757)	(0.766)	(0.763)	(0.592)	(0.598)	(0.719)	(0.713)
Mortality, 60-day	0.157	0.156	0.161	0.160	0.036	0.035	0.241	0.230
	(0.364)	(0.363)	(0.368)	(0.366)	(0.185)	(0.184)	(0.428)	(0.421)
Length of Stay	5.86	5.71	5.38	5.44	4.43	4.70	5.90	6.27
	(4.443)	(4.52)	(4.535)	(4.893)	(4.635)	(4.964)	(5.445)	(5.926)
Readmission, 30-day	0.151	0.148	0.222	0.217	0.167	0.157	0.211	0.196
	(0.358)	(0.355)	(0.415)	(0.413)	(0.373)	(0.364)	(0.408)	(0.397)

Table 3: Sample means and (standard deviations) of hospitals

Variable	All Hospitals	non-adopters	Adopters
Number of hospitals	2,953	2,650	303
Adjusted admissions	26,144	25,388	32,187
	(19,068)	(18,873)	(19,534)
System member	0.616	0.622	0.566
	(0.486)	(0.485)	(0.496)
Staffed beds	331	321	411
	(251)	(244)	(293)
For-profit	0.135	0.149	0.017
	(0.341)	(0.357)	(0.128)
Government-owned	0.104	0.102	0.121
	(0.305)	(0.302)	(0.326)
Nonprofit	0.761	0.749	0.863
	(0.426)	(0.434)	(0.344)
%Medicaid	0.161	0.160	0.172
	(0.114)	(0.112)	(0.127)
%Medicare	0.521	0.526	0.478
	(0.13)	(0.129)	(0.128)

From AHA and HIMSS data

Table 4: Fixed effects estimation of the impact of EMR and CPOE on patient outcomes

	PN	CHF	CA	AMI
	Mortality, 60-days (A)			
EMR & CPOE	-0.004	-0.001	-0.001	0.0002
	(0.002)	(0.002)	(0.001)	(0.003)
	Length of stay (B)			
EMR & CPOE	0.017	0.070*	-0.115	-0.051
	(0.035)	(0.035)	(0.063)	(0.060)
	Readmissions, 30-days (C)			
EMR & CPOE	0.000	0.001	0.006**	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	2,167,654	2,399,648	1,004,402	914,317

*Denotes significance at $p < 0.05$ and ** at $p < 0.01$
Key parameters from 12 regressions estimated by OLS including hospital and time fixed effects, errors clustered by hospital. Regressions each include the following demographic controls: female, white, female×white, age, age2, age3, white×age, female×age. Diagnostic controls: weighted counts of ADGs for current and prior admissions, primary diagnosis subcategory indicators (4-digits ICD-9 for AMI, CA, and CHF and 3-digits for PN), and secondary diagnosis indicators (AMI, PN, CA, CHF, diabetes, renal failure). Admission type indicators: emergent, urgent, and transfer. Hospital controls: adjusted admissions and multi-hospital system membership.

Table 5: Fixed effects estimation of alternative health IT measures on 60-day mortality

	PN	CHF	CA	AMI
Health IT application index (A)				
EMR & CPOE & EMAR & PACS	-0.006	-0.001	-0.001	0.0036
	(0.003)	(0.002)	(0.002)	(0.005)
Adoption and percent of utilization criteria met (B)				
EMR & CPOE	-0.001	-0.004	-0.003	-0.002
	(0.004)	(0.003)	(0.002)	(0.006)
(EMR & CPOE) × Utilization criteria met	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Adoption and % of pharmacy orders made electronically (C)				
EMR & CPOE	0.000	-0.006	-0.004	-0.004
	(0.004)	(0.004)	(0.002)	(0.006)
(EMR & CPOE) × % e-pharmacy orders	0.000	0.0001*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Cross-hospital Spillovers (D)				
EMR & CPOE	-0.0037	0.0009	-0.0011	0.0023
	(0.0028)	(0.0042)	(0.0016)	(0.0042)
Neighbor's EMR & CPOE (%)	0.0004	0.0008	0.0051	0.0033
	(0.0048)	(0.0042)	(0.0030)	(0.0077)
(EMR & CPOE) × (Neighbor's EMR & CPOE)	-0.0032	0.0001	-0.0012	-0.0269
	(0.0096)	(0.0086)	(0.0064)	(0.0194)
Observations	2,167,654	2,399,648	1,004,402	914,317

*Denotes significance at $p < 0.05$ and ** at $p < 0.01$

Key parameters from 12 separate regressions estimated by OLS with hospital and time indicators, errors clustered by hospital. Controls included: female, white, female×white, age, age^2, age^3, white×age, female×age, weighted count of ADGs for current and prior admissions, primary diagnosis subcategory indicators (4-digit ICD-9 for AMI, CA, and CHF and 3-digit for PN), secondary diagnosis indicators (AMI, PN, CA, CHF, diabetes, and renal failure), admission type indicators (emergent, urgent, and transfer) hospital adjusted admissions and a multi-hospital system membership indicator.

Table 6: Fixed effects estimation of EMR and CPOE adoption on 60-day mortality allowing for heterogeneous effects across patient severity

	PN	CHF	CA	AMI
Health IT interacted with severity (A)				
s_i	1.0165***	1.0102***	1.0151***	1.0182***
	(0.0010)	(0.0011)	(0.0025)	(0.0011)
EMR & CPOE	0.0092***	0.0083***	0.0049***	0.0094*
	(0.0023)	(0.0024)	(0.0014)	(0.0039)
(EMR & CPOE)$\times s_i$	-0.0905***	-0.0560***	-0.1788***	-0.0389**
	(0.0147)	(0.0147)	(0.0321)	(0.0126)
Health IT interacted with flexible function of of severity (B)				
EMR & CPOE	0.0091	(0.0063)	(0.0368)	0.0197
	(0.0121)	(0.0124)	(0.0208)	(0.0172)
$f_1(s_i)$	0.1405***	0.1128***	0.0571***	0.1709***
	(0.0020)	(0.0020)	(0.0027)	(0.0035)
$f_2(s_i)$	0.1773***	0.2265***	-0.1496***	0.3409***
	(0.0077)	(0.0084)	(0.0196)	(0.0131)
$f_3(s_i)$	-0.2521***	-0.2803***	0.5961***	-0.8084***
	(0.0278)	(0.0283)	(0.0458)	(0.0426)
EMR & CPOE$\times f_1(s_i)$	0.0039	-0.0050	-0.0172	0.0118
	(0.0080)	(0.0083)	(0.0091)	(0.0120)
EMR & CPOE$\times f_2(s_i)$	-0.0748	0.0238	0.0952	-0.0717
	(0.0360)	(0.0369)	(0.0801)	(0.0510)
EMR & CPOE$\times f_3(s_i)$	0.2307	-0.1335	-0.2530	0.2209
	(0.1331)	(0.1317)	(0.1944)	(0.1659)
Observations	2,167,654	2,399,648	1,004,402	914,317

*Denotes significance at $p < 0.05$ and ** at $p < 0.01$ and *** at $p < .001$
Key parameters from 8 separate regressions estimated by OLS with errors clustered by hospital. Difference-in-differences identification. The terms $f_1(s_i)$, $f_2(s_i)$, and $f_3(s_i)$ are generated by a fourth-order cubic spline of severity. These terms allow severity to have a flexible effect on mortality. Their interactions with EMR & CPOE adoption allow for heterogeneity in the effect of health IT on quality over the observable dimensions of severity.

Table 7: Fixed effects estimation of adoption of health IT, coordination, and information management on mortality

	PN	CHF	CA	AMI
s^c	1.0945***	1.0740***	1.0865***	1.0481***
	(0.0026)	(0.0022)	(0.0060)	(0.0032)
s^m	1.0170***	1.0213***	1.0097***	1.0059***
	(0.0025)	(0.0017)	(0.0053)	(0.0022)
s^o	1.0108***	1.0094***	1.0090***	1.0140***
	(0.0014)	(0.0016)	(0.0042)	(0.0016)
EMR & $CPOE$	0.0091**	-0.0038	0.0005	0.0189**
	(0.0032)	(0.0036)	(0.0022)	(0.0064)
$(EMR$ & $CPOE) \times s^c$	-0.0881**	0.0273	-0.0129	-0.1072*
	(0.0289)	(0.0273)	(0.0731)	(0.0444)
$(EMR$ & $CPOE) \times s^m$	-0.1111***	-0.0410	-0.1607*	-0.0558
	(0.0315)	(0.0231)	(0.0674)	(0.0289)
$(EMR$ & $CPOE) \times s^o$	-0.0585**	-0.0295	-0.1388*	-0.0055
	(0.0190)	(0.0200)	(0.0561)	(0.0201)
Observations	2,167,654	2,399,648	1,004,402	914,317

*Denotes significance at $p < 0.05$ and ** at $p < 0.01$ and *** at $p < .001$

Key parameters from 12 separate regressions estimated by OLS including hospital and time indicators, errors clustered by hospital.

Table 8: Fixed effects estimation of health IT and the role of learning, innovation, and adding leads to base specification

	PN	CHF	CA	AMI
Learning effects (A)				
EMR & CPOE	0.0052	0.0033	0.0043 *	0.0033
	(0.0037)	(0.0037)	(0.0020)	(0.0056)
$(EMR\ \&\ CPOE)_{t-2}$	0.0077	0.0057	-0.0004	0.0048
	(0.0042)	(0.0040)	(0.0023)	(0.0058)
$(EMR\ \&\ CPOE) \times s_i$	-0.0665**	-0.0307	-0.1668**	-0.0103
	(0.0222)	(0.0214)	(0.0606)	(0.0226)
$(EMR\ \&\ CPOE)_{t-2} \times s_i$	-0.0434	-0.0274	0.0330	-0.0254
	(0.0290)	(0.0253)	(0.0730)	(0.0263)
Innovation effects (B)				
EMR & CPOE	0.0055	0.0043	0.0037	0.0025
	(0.0037)	(0.0035)	(0.0021)	(0.0057)
$(EMR\ \&\ CPOE) \times (Adopt\ post\ '04)$	0.0068	0.0032	0.0007	0.0074
	(0.0041)	(0.0039)	(0.0022)	(0.0062)
$(EMR\ \&\ CPOE) \times s_i$	-0.0804**	-0.0318	-0.1543**	-0.0279
	(0.0219)	(0.0189)	(0.0595)	(0.0231)
$(EMR\ \&\ CPOE) \times (Adopt\ post\ '04) \times s_i$	-0.0158	-0.0217	0.0105	0.0040
	(0.0236)	(0.0208)	(0.0606)	(0.0233)
Incorporating leads of technology adoption (C)				
EMR & CPOE	0.0117**	0.0126**	0.0060 *	0.0055
	(0.0043)	(0.0038)	(0.0027)	(0.0063)
$(EMR\ \&\ CPOE) \times s_i$	-0.1430**	-0.0936**	-0.2100**	-0.0504**
	(0.0192)	(0.0188)	(0.0551)	(0.0190)
$(EMR\ \&\ CPOE)_{t+1}$	-0.0046	0.0041	-0.0014	-0.0011
	(0.0043)	(0.0035)	(0.0025)	(0.0055)
$(EMR\ \&\ CPOE)_{t+2}$	0.0068	-0.0082	0.0045	0.0082
	(0.0074)	(0.0051)	(0.0047)	(0.0086)
Observations	2,167,654	2,399,648	1,004,402	914,317

*Denotes significance at $p < 0.05$ and ** at $p < 0.01$.

See Table 7 footnotes for specification details.

Table A1: Effect of EMR and CPOE on inpatient outcomes without hospital FE

	PN	CHF	CA	AMI
	Mortality, 60-days (A)			
EMR & CPOE	-0.005*	-0.002	-0.002	-0.007*
	(0.002)	(0.002)	(0.001)	(0.004)
	Length of stay (B)			
EMR & CPOE	-0.210**	-0.043	-0.007	0.023
	(0.072)	(0.077)	(0.078)	(0.095)
	Readmissions, 30-days (C)			
EMR & CPOE	-0.001	0.000	-0.002	-0.003
	(0.002)	(0.003)	(0.004)	(0.005)
Observations	2,167,654	2,399,648	1,004,402	914,317

*Denotes significance at $p < 0.05$ and ** at $p < 0.01$
Key parameters from 12 separate regressions estimated by OLS with errors clustered by hospital. Regressions each include the following demographic controls: female, white, female×white, age, age2, age3, white×age, female×age. Diagnosis-based controls include: weighted count of ADGs, weighted count of ADGs for prior admission (conditional upon an admission within the past 6 months), primary diagnosis subcategory indicators (4-digit ICD-9 for AMI, CA, and CHF, and 3-digit for PN), and secondary diagnosis indicators (AMI, PN, CA, CHF, diabetes, renal failure). Admission type indicators included: emergent, urgent, and transfer. Hospital controls included adjusted admissions and multi-hospital system membership.