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INFORMATION TECHNOLOGY AND PATIENT HEALTH: ANALYZING OUTCOMES, POPULATIONS, AND MECHANISMS

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ABSTRACT

We study the effect of hospital adoption of electronic medical records (EMRs) on health outcomes, particularly patient safety indicators (PSIs). We find evidence of a positive impact of EMRs on PSIs via decision support rather than care coordination. Consistent with this mechanism, we find an EMR with decision support is more effective at reducing PSIs for less complicated cases, using several different metrics for complication. These findings indicate the negligible impacts for EMRs found by previous studies focusing on the Medicare population and/or mortality do not apply in all settings.

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1. Introduction

The increasing availability and adoption of electronic medical records (EMRs) of various forms has generated substantial optimism concerning possible consequent improvements in productivity, costs, and quality within the healthcare sector (e.g., Hillestad et al., 2005). This optimism has proven substantial enough to even spur the passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act in 2009, which includes substantial financial incentives for adoption. In contrast, the extant literature measuring various impacts of EMR adoption provides little indication of dramatic returns (e.g., Ahga 2014, McCullough et al. 2010, McCullough et al. 2013, Parente and McCullough 2009). However, the scope of these analyses, particularly with regard to health outcomes, has largely been limited due to data constraints. In particular, previous studies have focused on mortality among Medicare patients as the primary health outcome, and large-scale studies generally have focused only on the Medicare population. The lone large-scale study that we are aware of using data from non-Medicare patients is Miller and Tucker (2011), who find that the availability of EMRs within a county decreases infant mortality rates.

In this study, we build and utilize a newly integrated dataset to analyze the effect of EMR adoption on health outcomes for a broader patient population, and for less severe, more common adverse health outcomes known as patient safety indicators (PSIs). Our data allow us to examine whether EMR adoption impacts PSIs for the general population, and whether the size of the impact varies according to a patient's level of "complication," measured in several different ways. Further, by examining multiple health outcomes (i.e., PSIs, inpatient mortality, and length of stay), different types of EMRs, and accounting for differing levels of patient complication, we are able to learn more about potential mechanisms through which EMRs impact health outcomes.

In particular, EMRs may impact health outcomes via decision support and/or care coordination, and these mechanisms, if at work, have different implications based on health outcome, EMR, and patient complication. We can then test these implications against what we observe in the data to distinguish the channels through which EMRs have an impact.

Expanding the population and type of health outcome for which we have an empirical assessment of EMRs' effectiveness, along with an improved understanding of the mechanisms by which they operate, can have a significant impact on public policy and subsequent EMR research. It can have a powerful impact on how the U.S. government should be setting policy as pertains to EMR. In particular, it will help to better assess the potential social value of incentive programs and whether targeted incentives may be warranted. Further, it can help inform hospitals' adoption decisions and potentially patients' choice of hospitals.

To our knowledge, our study is the first that combines data on EMR adoption with a nationally representative sample of hospital discharges and examines the effects of hospital EMR adoption on such a broad patient population. Our primary data sets include the 2003 through 2010 Health Information and Management Systems Society (HIMSS) Analytics Database and the Nationwide Inpatient Sample (NIS) collected by the Agency for Healthcare Research and Quality's (AHRQ) Healthcare Cost and Utilization Project (HCUP). Beyond construction of a novel and integrated dataset, the other primary innovation of our study is the direction in which it takes analysis of the effects of EMR adoption. Prior work has consistently analyzed the effects of EMR adoption for very specific subgroups of the population – in particular, the senior population or very small groups of hospitals. Like McCullough et al. (2013), which does explore heterogeneity of impacts within the Medicare population, our study calls attention to the real and consequential possibility that EMR adoption may have different impacts across various population subgroups depending on the underlying mechanisms.

To test for the effect of EMR adoption on PSIs, we employ a fixed effect approach, exploiting the fact that many hospitals adopted new EMR systems during our time period. We are therefore able to control for fixed differences between adopting and non-adopting hospitals and identify how adopting an EMR changes PSI rates within the adopting hospital. In addition to estimating the overall effect of EMR adoption on PSIs, we estimate the relationship separately according to patient complication (measured by age, complexity, diagnosis commonality, and severity). Our empirical analysis focuses on two EMR applications, Computerized Physician Order Entry (CPOE) and Physician Documentation, which have experienced significant increases in adoption during our study period. We find that CPOE significantly decreases the occurrence of preventable adverse events as measured by PSIs for non-complicated cases. For example, CPOE is associated with a 12% drop in the probability of experiencing at least one postoperative adverse event for cases with no more than one comorbidity.

This finding stands in contrast to previous results focusing on mortality as an outcome and suggests that EMRs indeed have important effects on patient outcomes less severe than mortality. Assuming decision support is more likely to be helpful for less complicated cases, in which standard treatment guidelines can play a larger role relative to care coordination, this finding is also suggestive of decision support playing an important role in EMR effectiveness. This notion is further corroborated by the fact that we do not find comparable effects for Physician Documentation, given CPOE is more amenable to decision support while Physician Documentation is more amenable to care coordination.

Our findings suggest interesting implications about the effectiveness of EMRs in improving health outcomes and provide an important new set of findings to complement the growing literature on the effect of EMRs on health outcomes. First, our findings suggest that EMRs play a role in improving patient wellbeing by decreasing preventable adverse events among the non-senior population. A significant group of previous studies has focused largely on the senior population and has lacked strong evidence of quality improvement.[1] For example, Agha (2014) finds little effect of EMR adoption on patient mortality, medical complication rates, adverse drug events, and readmission rates. McCullough et al. (2010) find some evidence of improvement in quality measures, but temper this finding by concluding that achieving substantive benefits from EMR adoption at a national level may be a lengthy process. Parente and McCullough (2009) find some improvement in patient safety due to EMR adoption, but conclude there is not enough evidence to draw a strong link between EMR and improvements in patient safety for the Medicare population.[2] Different from these studies, our paper examines health effects for a broadly defined, nationally representative population. In addition, we focus on patient safety, which is arguably a more relevant measure for the non-senior population and can shed light on the impacts of EMRs on important, but non-deadly, adverse health events.

Second, our results highlight the importance of exploring heterogeneity among population subgroups, especially when considering different mechanisms through which EMRs may be expected to impact different patients. Our finding that some EMR applications are more impactful for less complicated patients suggests that the decision support functions of EMRs do lead to improved patient outcomes. This finding complements previous findings of McCullough

[1] Other studies on health outcomes have included the non-senior population and found more positive findings, but have utilized small, focused sets of data, primarily within a single hospital setting (e.g., Bates et al. 1998, Bates et al. 1999, and Simeonova and Koulayev 2013).
[2] Their study was limited to a sample of Medicare patients during 1999 and 2002. They also study a different set of EMRs such as nurse charts and picture archiving and communications systems.

et al. (2013), who explore heterogeneity for four high-frequency and high-severity diagnoses within the Medicare population. They find that EMRs reduce mortality for the highest severity Medicare patients, particularly those with diagnoses that require information management and care coordination. Our inclusion of a younger, less complex patient population and focus on outcomes for which decision support may be more beneficial allows us to empirically assess an additional channel through which EMRs improve patient care. Taken together these studies suggest that advanced EMRs can be beneficial beyond basic patient data collection. Moreover, EMRs are likely to impact different types of patients through different mechanisms.

Third, our paper is also related to the existing studies on the effect of EMRs on cost of care. Despite some relatively sanguine findings concerning costs (e.g., Wang et al. 2003 and Chaudhry et al. 2006), the majority of the literature suggests cost savings have been small or non-existent (see Sidorov 2006 for a literature review and Agha 2014 for a more recent study). It is noteworthy that Dranove et al. (2012) find that EMRs, on average, generate a slight increase in operational costs. However, this average effect is a combination of cost reductions for hospitals in “favorable” locations (i.e., due to IT complementarities) and large cost increases for hospitals in “unfavorable” locations. As discussed below, patient safety indicators have been linked to longer hospital stays and higher hospital charges (Zhan and Miller 2003). Therefore, our results also have implications for EMRs’ role in reducing the cost of care by limiting adverse events with additional downstream costs.

Our paper lastly contributes to the broader literature on the effect of information technology (IT). In the healthcare setting, Athey and Stern (2002) find IT linking 911 caller identification to a location database speeds emergency response and reduces short-term mortality and hospital costs. Javitt et al. (2008) examine a randomized implementation of decision support tools within an HMO population and find that these tools reduce costs and improve quality. IT has also been studied in other settings such as banking (Autor et al. 2002) and trucking (Baker and Hubbard 2003 and Hubbard 2003). Particularly, Autor et al. (2003) find that IT substitutes for labor in routine tasks and complements labor in non-routine tasks which involves problem-solving and complex communication. In our study, we find that EMRs improve health outcomes through clinical decision support, a mechanism consistent with complementarities between IT and skilled labor inputs. Our findings also have potentially broader implications in light of recent work distinguishing communication technologies from information technologies (Bloom et al. 2014). Specifically, it is natural to view EMRs facilitating care coordination as communication technologies, and EMRs facilitating decision support as information technologies. Bloom et al. (2014) find that the former technologies work toward firm centralization while the latter work toward firm decentralization. To the extent that this insight applies to hospitals, our findings suggest that the EMRs tending toward decentralization (CPOE) have proven particularly effective, at least for some health outcomes.

2. Electronic Medical Records and Health Outcomes

2.1. What are EMR Technologies?

As noted in Dranove et al. (2012), an electronic medical record (EMR) is a "catchall expression used to characterize a wide range of technologies used by hospitals to keep track of utilization, costs, outcomes, and billings." Some technologies generally classified as EMRs include: Enterprise EMR, Clinical Data Repository (CDR), Clinical Decision Support System (CDSS), Order Entry, Computerized Practitioner Order Entry (CPOE), and Physician

Documentation. Wang (2012) considers all six of these technologies in her analysis, and Dranove et al. (2012) consider all but Enterprise EMR.

The functionality of these EMR technologies perhaps is best presented via categorization. Both Dranove et al. (2012) and Wang (2012) break EMR technologies into two broad groups, which can essentially be labeled "basic" and "advanced." The basic group includes Enterprise EMR, CDR, CDSS, and Order Entry, and the advanced group includes CPOE and Physician Documentation. As Wang (2012) describes, this basic group contains applications that "can be used to store, organize and retrieve patients' information" and the advanced group presents medical history, recommends drugs, and helps health care providers make better decisions. Dranove et al. (2012) note that these advanced applications "are more difficult to implement and more difficult to operate successfully due to the need for physician training and involvement."[3]

We focus our analysis on more advanced applications (CPOE and Physician Documentation) for two reasons. First, as detailed in Section 3, diffusion of more advanced technologies is more relevant to our study period, which covers more recent years than many previous studies. Second, recent policy incentivizing EMR adoption and utilization requires providers to demonstrate advanced capabilities above and beyond digitization of patient data. Our main analysis examines CPOE specifically, as it is expected to have direct links to patient outcomes. As described in McCullough et al. (2013), CPOE allows physicians to directly input orders, potentially reducing miscommunication and errors. Additionally, rules-based protocols, treatment guidelines, and prescription error checking are often built into CPOE products.[4] These

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[3] It is worth noting that Agha (2014) has a slightly different means of characterizing these technologies. Her first group consists of applications whose primary functions are record keeping; and the second being Clinical Decision Support (CDS) whose primary functions are decision support.

[4] CDSS application can also provide diagnosis and treatment recommendations based on clinical information. As in McCullough et al. (2013) we do not focus on the CDSS application itself due to inconsistent reporting in the HIMSS data.

types of features that provide automatic reminders, check lists, and error checking may be expected to have direct impacts on preventable adverse events that the patient safety indicators we examine are intended to measure.

In addition to CPOE, we also provide separate analyses for Physician Documentation. Physician Documentation allows physicians to input information. It also generates diagnostic codes from clinical information. These codes can be used both for billing purposes, but also to enhance communication between practitioners through standard coding (Dranove et al. 2012). Physician Documentation may be expected to reduce adverse events when care is administered by multiple practitioners who must communicate efficiently and coordinate a patient's care.

2.2. Why Do Hospitals Adopt EMR Technologies?

The primary reasons cited for hospitals to adopt EMR technologies revolve around healthcare quality and costs. For example, President Obama stated on January 8, 2009 the following: "To improve the quality of our health care while lowering its cost, we will make the immediate investments necessary to ensure that within five years, all of America's medical records are computerized. This will cut waste, eliminate red tape, and reduce the need to repeat expensive medical tests. But it just won't save billions of dollars and thousands of jobs – it will save lives by reducing the deadly but preventable medical errors that pervade our health care system."

Adoption of EMRs can reduce costs for hospitals by eliminating redundancy, as noted by the President. Further, as noted in Hillestad et al. (2005), EMR adoption can lower costs by reducing drug, radiology, and laboratory usage, reducing clerical staff, reducing nursing time, lowering medical errors, and shortening inpatient lengths of stay. Adoption of EMRs can improve healthcare quality by reducing errors and improving disease prevention and chronic disease management (Hillestad et al., 2005). In addition to these direct benefits to an adopting hospital, as Wang (2012) notes, EMR adoption may generate externalities, meaning its value to one hospital depends on the adoption decisions of other hospitals. Specifically, the value of adopting EMR for a given hospital may increase as a function of the number of other hospitals with EMR, since information transfer becomes easier as more hospitals participate. However, the opposite may be true if EMR adoption attracts more patients, such that ultimately the profits of adoption decrease as the number of adopters increases.

In deciding whether to adopt EMRs, a hospital must balance the above (potential) benefits against the costs of adopting. The Congressional Budget Office (CBO, 2008) estimates the cost of EMR adoption for a typical urban hospital to range between $3 and $9 million, along with between $700,000 and $1.35 million per year for maintenance. The costs and benefits of adoption certainly change over time, as do awareness levels across hospitals and patients. Hence, as we discuss in Section 3, there is significant variation in hospitals' timing of adoption of EMR technologies. This variation is important for us to identify the health effects of these technologies, and our econometric methods are designed to account for potential factors that may concurrently influence EMR adoption and health outcomes, as we discuss in our Methods section.

2.3. What are Patient Safety Indicators?

Developed by AHRQ, patient safety indicators (PSIs) are intended to measure preventable in-hospital complications and adverse events. These indicators are well-defined and have gained traction as a health outcome of interest in the general literature on policy interventions and hospital quality of care (e.g., Iizuka 2013).

Using PSIs as measures of patient outcomes is one important innovation of our study. PSIs comprise a particularly important set of outcomes for the purpose of identifying the effect of EMR adoption. These measures have the advantage of being more variable than other health outcome measures such as mortality, and allow us to examine the effects of EMRs on meaningful health outcomes that are less severe than mortality. Patient mortality has been commonly used as a reliable indicator for quality of care, especially for the elderly and severely sick population. However, being an extreme outcome measure, patient mortality might fail to capture improvement in health outcomes resulting from EMR adoption if patients most likely to be impacted by EMRs are not sick enough to experience mortality. As we discuss below, this might be particularly true for patients most impacted by clinical decision support aspects of EMR technologies.

In addition to representing a significant indicator of patient well-being, PSIs are linked to increased healthcare utilization and cost. Zhan and Miller (2003) use the 2000 Nationwide Inpatient Sample to examine how adverse events measured by patient safety indicators impact health care utilization and eventual mortality. They use a multivariable matching estimator to compare length of stay, hospital charges, and in-hospital mortality for patients experiencing an adverse event to observably similar patients within the same hospital not experiencing an adverse event. They find statistically significant differences in these three outcomes for all of the PSIs that we examine in this paper. For example, they find that patients with postoperative pulmonary embolism or deep vein thrombosis spend 5.36 additional days in the hospital, have higher hospital charges by $21,709, and have a 6.56% higher in hospital mortality rate. While these differences may be partially driven by unobserved severity, they motivate that PSIs have important implications for downstream health care utilization and costs, and in addition to representing decreased patient well-being, can lead to potential increases in mortality.

We focus our analysis on the following four PSIs: postoperative hemorrhage or hematoma, postoperative physiologic and metabolic derangement rate, postoperative respiratory failure rate, and postoperative pulmonary embolism or deep vein thrombosis. In presenting our main results, we aggregate these into a single measure of those experiencing at least one of these four postoperative adverse events. We make our choice of PSIs based on the opinion of clinical experts, following the strategy of Parente and McCullough (2009).[5] Particularly, we have chosen PSIs that are most likely to be impacted by the availability of EMRs, in particular those that measure adverse events that can be prevented by checklists and reminders and/or by the provision of the detailed clinical information regarding the patient. We exclude from our analysis PSIs that occur with extremely low incidence such as deaths in low mortality diagnosis-related groups.

In addition to examining this set of PSIs that are most likely to be directly linked to EMRs, we also examine a number of PSIs that measure adverse events tied more directly to surgical skills and physical accidents. We present results of these PSIs as a falsification test. Appendix Table 1 provides definitions of all of the PSI outcomes used in our analysis.

2.4. Mechanisms and Possible Heterogeneous Effects of EMR Adoption

[5] As mentioned above, one prior study by Parente and McCullough (2009) has analyzed the effect of EMR adoption on PSIs. The PSIs they utilized were: infection due to medical care, postoperative hemorrhage or hematoma, and postoperative pulmonary embolism or deep vein thrombosis. We look at a broader list of PSIs; however, due to data changes, we do not include infection due to medical care.

We largely follow McCullough et al. (2013) in discussing two main channels through which EMRs are expected to impact health outcomes: clinical decision support and information management/care coordination. Clinical decision support includes a variety of tools that, in conjunction with patient data, can supply the provider with rules-based protocols, treatment guidelines, and error checking. Information management and care coordination are related mechanisms through which EMR technologies can assist providers in monitoring large amounts of clinical data about their patients and in coordinating treatment between multiple providers.

These mechanisms each lead to different predictions about which types of patients may benefit most from EMR adoption. McCullough et al. (2013) suggest that decision support may be most beneficial for moderate to low complexity patients, arguing that "Standard treatment guidelines are rarely implemented for complex combinations of diagnoses." In other words treatment guidelines, protocols, and reminders are less beneficial when providers must care for patients with multiple interacting conditions and complexities.

While this may seem counterintuitive, rule based decision making that can be aided by decision support systems are most effective when a simple rule is available for a well-defined problem (Musen et al. 2006). The field of bioinformatics continues to struggle with the design and implementation of decision support systems for patients with multiple comorbidities. Therapeutic plans and clinical guidelines are typically disease specific without clear recommendations for handling comorbidities (Jafarpour and Abidi 2013). There is concern that some decision support systems may in fact present harmful advice if they do not properly account for comorbidities (Fraccaro et al. 2015). While the field of informatics is making progress in developing methods for merging clinical guidelines in decision support systems

(Jafarpour and Abidi 2013), this area has been identified as a “grand challenge” in the field of decision support (Sittig et al. 2008) and remains under investigated (Fraccaro et al. 2015).

Alternatively, information management and care coordination mechanisms are most likely to play a role in high complexity patients, particularly those with conditions that involve synthesizing a large amount of clinical information or many different types of providers. McCullough et al. (2013) find EMRs to have no overall impact on mortality among Medicare patients, but evidence that EMRs improve mortality for the highest severity patients. They further decompose these effects and find the largest benefits for patients with conditions most relevant to information management and care coordination.

While McCullough et al. (2013) do not find empirical evidence for the prediction that decision support applications have meaningful health effects in less complex cases, our context may lead to different results since our analysis uses a more diverse patient population and an outcome measure that is arguably more amenable to a decision support function. With regards to patient population, older patients on average are likely to have greater complexity, therefore leading decision support to be a potentially more important mechanism for younger patient populations. For example, a previous study by Javitt et al. (2008) finds improvements in quality of care from decision support in an HMO population of patients all less than 65 years of age.

We might also expect different outcomes to respond differentially to these mechanisms. In particular, patient safety indictors might better capture differences in health outcomes for less complex cases as compared to mortality. Therefore, by examining these less severe, but medically meaningful outcomes, we may be able to better detect the effects of decision support on care quality. For example, decision support may prompt physicians to order anticoagulants in order to prevent deep vein thrombosis (measured in PSI 12) among surgical patients

(McCullough et al. 2013). In addition to patient safety indicators, we also examine alternative outcomes such as inpatient mortality, which may be a more relevant outcome for higher severity patients. Comparing the impact of EMRs on patient safety indicators and inpatient mortality could help shed light on the underlying mechanism, since the former could be relatively more driven by decision support and the latter relatively more driven by care coordination.

Finally, these mechanisms also point to potential differential effects by type of EMR technologies. Whereas both technologies we study can contribute to both decision support and care coordination, they have different primary focuses. CPOE provides a platform by which the physician directly interacts with the IT system to submit orders, and decision support is often incorporated into the CPOE interface. In contrast we expect the adoption of Physician Documentation to be more relevant to the care coordination mechanism through its ability to allow physicians to clearly document and communicate patient information.

3. Data

3.1. Data Construction

The data we use come from several sources, and to our knowledge, this is the first study using such integrated data. Our first source of data is the Healthcare Information and Management Systems Society (HIMSS) Analytics Database. HIMSS conducts an annual survey of health care providers, including over 3,000 hospitals nationwide with more than 100 beds. The survey collects a wide range of information on more than 100 different health information technology applications, including CPOE and Physician Documentation. For each of these applications we construct variables for whether or not a hospital has installed a system in a given year.[6] The HIMSS data we have span the years from 2003 to 2010.

Our second data source is the Nationwide Inpatient Sample (NIS), collected by the Agency for Healthcare Research and Quality's (AHRQ) Healthcare Cost and Utilization Project (HCUP). The NIS is a 20-percent, nationally representative, stratified sample of U.S. community hospitals. Since NIS includes the universe of inpatient discharge records from these sampled hospitals, we are able to observe both Medicare and non-Medicare insured patients. For each discharge record, the data set includes information such as diagnosis and procedure codes, admission and discharge status, patient demographics, expected source of payment, length of stay, and hospital charges. The NIS also reports basic hospital characteristics including size, location, ownership type, and number of total discharges.

NIS provides detailed patient data to build measures of Patient Safety Indicators (PSIs), our main outcomes of interest. We calculate these indicators using a module provided by AHRQ. This module uses information in the discharge record, such as age, diagnosis related groups, diagnosis codes, and procedure codes to identify the subpopulation of patients for whom a particular adverse event is relevant and those who have experienced the adverse event. For example, for the PSI indicating Postoperative Hemorrhage or Hematoma, the module first identifies patients who have received operations and might be at potential risk, and then it determines which of these patients have experienced a hemorrhage or hematoma.

We supplement the HIMSS and NIS data with American Hospital Associate (AHA) data. The AHA data is used to build a crosswalk between the HIMSS and NIS data. The only external hospital identifier in the HIMSS data is the hospital's Medicare provider numbers. The only

[6] Following the guidance from HIMSS, we consider an application as installed if its status in the HIMSS data is live and operational, automated, to be replaced, or replaced.

external hospital identifier in the NIS data is the hospital's AHA ID number. AHA data contain both identification numbers, thus allowing us to merge the HIMSS and NIS data at the hospital-year level.

Ultimately, our merged sample includes more than 9.1 million patient observations from a total of 1,896 unique hospitals in 29 states. [7] Table 1 provides a comparison of our sample to the universe of the hospitals from these 29 states and from all states. Overall our sample is slightly weighted toward nonprofit, large, teaching hospitals in urban areas, partly due to the NIS sampling design and the availability of the AHA ID number, but provides a general representation of US hospitals.

[Table 1 about here]

While the NIS is not a panel of hospitals, a large fraction of hospitals appear in the data in multiple years. In our final sample spanning from 2003 to 2010, we observe 1,133 unique hospitals that appear at least twice.[8] This allows us to relate changes in patient safety to changes in EMR adoption within hospitals and over time. Others have used the fact that hospitals appear in the NIS in multiple years to exploit within-hospital changes in other contexts (e.g. Kolstad and Kowalski, 2012).

3.2. Construction of Key Variables

[7] Note that AHA identification numbers are only available for hospitals from a subset of states in the NIS, as some states have not authorized HCUP to release information that would specifically identify hospitals. We observe 3,858 unique hospitals in the 2003 to 2010 NIS data. Of these, 2,377 unique hospitals have AHA identification numbers available in the data. We are able to merge 1,922 of these hospitals to the HIMSS data.

[8] The sample size for each regression described below varies, as the number of patients at potential risk for each PSI may differ.

Our main analysis focuses on an aggregate PSI which equals 1 if a patient experiences any of the four postoperative adverse events expected to be linked to EMRs (PSI9, PSI10, PSI11, and PSI12). We are interested in exploring whether EMR adoption has heterogeneous effects based on patients' levels of complication. To this end, we use a variety of proxies to measure various metrics of complications, including case complexity, diagnosis commonality, mortality risk, and functional severity. To measure complexity, we use information on a patient's comorbidities. We define a less complex patient as one having no more than one comorbidity. To measure diagnosis commonality, we utilize diagnosis-related group (DRG) information. We consider a patient with a DRG code among the top 20 most frequent DRGs for each PSI under study to be more common. To measure risk and severity, we use data available in the NIS severity files that differentiate patients by their mortality risk and their loss of function.[9] Regarding risk type, we define low mortality risk cases as those with a "minor likelihood of dying" and high risk cases as those with "moderate", "major" or "extreme likelihood of dying." Regarding severity, we define low severity cases as those with "minor loss of function" and high severity cases as those with "moderate," "major" or "extreme loss of function."

We also consider patient age, which can serve as a proxy for complication along all four of the above categories. This is because we expect that the non-elderly, on average, present simpler, more common, less risky and less severe cases. An additional advantage of exploring heterogeneity by age is that our results can be directly compared to existing studies which have focused on the elderly population alone through their focus on Medicare data.

[9] The two variables names used are APRDRG_Risk_Mortality and APRDRG_Severity. They are assigned using software developed by 3M Health Information Systems. Their calculation includes the base APR-DRG, the severity of illness subclass, and the risk of mortality subclass within each base APR-DRG. For more information, please refer to the HCUP User Support Website (www.hcup-us.ahrq.gov).

3.3. Summary Statistics

Table 2 shows the fraction of hospitals in our analysis sample that have adopted CPOE and Physician Documentation by year. CPOE adoption rates grew from 7% to 31% from 2003 to 2010. Physician Documentation grew from 18% to 39% from 2005 to 2010.[10] This rapid diffusion provides the key variation we use to identify the effect of EMR adoption on patient safety.

[Table 2 about here]

Table 3 presents summary statistics of our PSI measures. For each PSI used in our analysis, a value of 1 indicates a patient experiencing an adverse event. Note that sample size varies across PSIs because the set of patients that are potentially at risk of each adverse event is different. In Table 3, we present the mean value of each PSI, which indicates the average rate of occurrence among its relevant population. For example, for Agg PSI, the aggregate PSI, we observe an average of 1.81% with a standard deviation of 13.31%. In our sample, with a total of 9.1 million patients at potential risk, it suggests that about 165,000 patients had experienced at least one of the adverse events.

[Table 3 about here]

[10] Note that Physician Documentation was first added to HIMSS in 2005. We are able to uncover the status of adoption in 2003 and 2004 for non-adopters (those that did not adopt between 2005 and 2011) and late-adopters (those that adopted between 2005 and 2011). For those that we observe adoption in 2005, we are not able to tell the year of adoption so we do not fill in these missing values.

Table 4 provides summary statistics of the aggregate PSI by patient complication. Not surprisingly, we find that the rate of occurrence of adverse events is lower for less “complicated” patients; however, PSIs are still meaningful health outcomes for less complicated patients as defined by most of our proxies. For example, nonelderly patients have a mean of 1.49% while elderly patients have a mean of 2.21%. Similarly, the mean is 0.53% for low-mortality-risk patients but as high as 4.02% for high-mortality-risk patients. We also explore how our measures of complication overlap with each other. We find that among the ten correlation coefficients between these measures, eight are smaller than 0.25. The remaining two are 0.36 (between low mortality and common DRG) and 0.49 (between low mortality and low severity). These numbers suggest that our measures for case complication seem to provide meaningful variation along different dimensions.

[Table 4 about here]

4. Empirical Model

Our general empirical strategy for testing the impact of EMR adoption is to relate within-hospital changes in patient safety over time to within-hospital changes in the availability of EMRs. Hospitals that do and do not have EMRs may be very different from each other. Therefore it is important to exploit over time variation in EMR adoption. The key identifying assumption is that trends in the prevalence of PSIs are not correlated with unobserved adoption trends. In other words, our empirical strategy hinges on the idea that when a hospital adopts EMRs there are no concurrent events, left unaddressed by our controls, that would have an impact on patient safety. If this assumption is satisfied, we can attribute changes in patient safety to EMR adoption. McCullough et al. (2013) and Agha (2014) provide extensive evidence that EMR adoption is unlikely to be correlated with pre-existing trends in patient outcomes or severity in the Medicare context. In results shown below we perform a variety of tests to ensure this assumption is likely to hold in our empirical context as well.

Our baseline empirical specification follows a linear probability model, with hospital and time fixed effects:

$$PSI_{iht} = \beta_0 + \delta_t + \alpha_h + Z_{iht}\beta_1 + \beta_2 EMR_{ht} + \beta_3 EMR_{ht} * X_{iht} + X_{iht}\beta_4 + X_{iht} * I\_year + \varepsilon_{iht}$$

$PSIi_{ht}$ represents the occurrence of an adverse event for patient *i* in hospital *h* during year *t*. $\alpha_h$is a set of hospital fixed effects, δ_t is a set of year fixed effects, and Z_{iht} stands for a set of patient-level control variables, including age, age squared, gender, race dummies, payment dummies, risk dummies, severity dummies, and 27 different comorbidity dummies as defined by AHRQ.[11] EMR_{ht} is a dummy variable for the presence of an EMR system installed in hospital *h* at year *t*.[12] X_{iht} is one of the following dummies to represent patient heterogeneity: non-elderly, non-complex, common DRG, low-mortality risk, and non-severe case. We interact each dummy variable (X_{iht}) with the EMR_{ht} dummy to allow the effect of EMR to differ on the basis of patient heterogeneity. We also include group specific year fixed effects ($X_{iht} * I\_year$) to allow outcomes to differ arbitrarily between each group over time.

We are particularly interested in the estimates of β_2, which measures the overall effect of EMR adoption, and β_3, which measures whether the effect varies by patient complication level. In addition, β_4 measures whether patient safety indicators vary based on patient complication level itself. The estimation of the model uses discharge weighting and standard errors are

[11] All of our results hold if we include some hospital level controls such as hospital bed size, urban vs. rural location, and ownership type.
[12] Adding additional controls such as state-year fixed effects and differential trends based on hospital characteristics such as teaching status produce largely similar results. See more discussion in Section 5.2 where we address endogeneity concerns.

clustered at the hospital level.[13] We provide separate analyses for CPOE and Physician Documentation. Note that the results of the effect of each application do not change if we analyze both EMRs jointly within the same regression.

We also extend our baseline model in a number of ways. First, we explore how the impact of EMR adoption on patient safety differs by time since adoption. For this analysis we replace the EMR dummy with three different dummies indicating the first, second, or third or more year of adoption. This specification allows for the fact that it may take time to fully and optimally incorporate EMR usage into practice patterns. Coefficient estimates from this specification reveal how this process evolves from the first year of adoption through later years. Second, in related specifications, we include dummies for years prior to adoption to test the identifying assumption that adopting hospitals do not have differing pre-adoption patient safety trends. Last, we further explore heterogeneity by examining a three-way interaction of EMR application, non-elderly and non-complicated case. Our baseline model differentiates patients along a single dimension of heterogeneity. This extended model allows for an additional interaction between age and level of complication to test if the effect of EMRs differs by complication within age groups.

5. Results

5.1. Main Results

We first report our main results for CPOE in Table 5. Note that for ease of presentation, we multiply all coefficients and standard errors by 100. We find an overall negative but statistically insignificant effect of CPOE on the probability of experiencing an adverse event.

[13] Weights are provided in the NIS data and are intended to produce nationally representative estimates, accounting for the sampling frame.

Allowing for heterogeneous effects by patient age (column 1), we find that CPOE has a larger effect on non-elderly patients, suggesting that non-elderly patients are likely to benefit more from CPOE adoption. We also observe consistent patterns of results when examining heterogeneous effects along other dimensions. We find that complicated cases are not affected by CPOE; however, non-complicated cases do experience large decreases in PSI occurrences. All interaction effects are large in magnitude and statistically significant. The F-statistics reported in this table allow us to reject the hypothesis that the overall effects for less complicated patients (main effects of CPOE plus interaction effects) are equal to zero. To be more specific, the adoption of CPOE is associated with a 12% ((0.016-0.180)/1.34) drop in the probability of experiencing at least one postoperative adverse event for cases with no more than one comorbidity (non-complex). We find no significant effect of CPOE on patients with less common DRGs; however, patients that are diagnosed with more common DRGs experience a 20% ((-0.14-0.033)/0.86) decrease in the probability of an adverse event with the adoption of CPOE. Similarly we find a largely lowered rate of adverse events for patients with low mortality risk and low severity.[14]

[Table 5 about here]

The pattern of estimates observed in Table 5 suggests the importance of allowing for heterogeneity when examining the effect of CPOE adoption. Since these measures of case

[14] The percentage declines for these last two measures are 43% and 135%, respectively. We acknowledge that these percentage figures are high, and likely due to the fact that these two events have particularly low means and we are using a linear probability model (which does not force probabilities to be above zero). We have attempted to run these two models in particular using a logit framework; however, they do not converge due to the very large number of fixed effects. Nevertheless, we note that these results, while quantitatively high in percentage terms, qualitatively line up with our results for the other higher-probability events we analyze.

complication provide variation along different dimensions, finding qualitatively consistent results among them also suggests that CPOE is more likely to improve patient outcomes for less complicated cases through the clinical decision support mechanism.

To get a sense of how these improvements in PSIs translate to reduction in healthcare costs, we conduct a back-of-envelop calculation using data from Zhan and Miller (2003). For example, Zhan and Miller (2003) find that patients that have experienced postoperative respiratory failure are associated with an excess charge of $74,052 in 2014dollars. They also provide the amount of excess charge for the other three PSIs used in our study. Since we focus on the aggregate PSI, we calculate the average excess charge across the four PSIs, which amounts to $52,409 in 2014 dollars. Zhan and Miller (2003) also find that these PSIs increase hospital stays by 6.81 days on average. According to the NIS 2010 data, a total of about 8.1 million patients nationally were at potential risk of experiencing any of the four postoperative adverse events. Of this 8.1 million, 3.89 million, 2.43 million, 4.94 million, and 2.84 million are of low-complexity, common DRG, low-mortality risk, and low severity respectively. Our results suggest that CPOE decreases the probability of such adverse events by 0.164 percentage points for non-complex patient (Column 2 of Table 5), translating to 6,376 prevented adverse events per year based on the number of low-complexity patients in the 2010 NIS. This amounts to a total of more than $334 million in hospital charges (or 43,423 inpatient days) for those affected non-complicated cases in 2010. Depending on the model specification that we use, these figures range from savings of $220 million (or 28,629 inpatient days) if we focus on common-DRG cases to about $590 million (or 76,717 inpatient days) for low-mortality cases. These calculations suggest that CPOE is associated with a large decrease in hospital charges and inpatient length of stays. Note that since our main outcome variables are relevant for a subgroup of the patient population, those numbers represent part of the potential savings associated with EMRs.

We report the same set of results for Physician Documentation in Table 6. We find less pronounced effects for Physician Documentation, although the pattern of heterogeneous effects is similar to the findings for CPOE. Physician Documentation is found to significantly reduce the occurrence of adverse events only for patients with low mortality risk (column 4). As indicated in Section 2, there is reason to believe CPOE and Physician Documentation may have differing impacts on health outcomes, since the former has more capability toward clinical decision support and the latter toward care coordination.

It is important to note that for all the analyses reported in the paper, combining CPOE and Physician Documentation in the same regression provides similar results. For the remainder of the paper, we focus our analysis on CPOE, since it is the EMR, of the two, that appears to display a notable impact on PSIs.[15]

[Table 6 about here]

5.2. Endogeneity Concerns

In this section, we first discuss and address potential endogeneity issues resulting from unobserved heterogeneity between adopting and non-adopting hospitals. We then explore whether patient composition changes following the adoption of EMRs, which might also cause bias in our estimation.

[15] The full set of results with both CPOE and Physician Documentation in the same regressions are available upon request.

The fact that hospitals actively decide to adopt CPOE or any type of EMR applications poses concerns about potential bias. In our main specification, we use hospital fixed effects to account for the fact that adopting and non-adopting hospitals may differ in terms of baseline characteristics. Therefore, our key identifying assumption is that hospitals that adopt during our sample period do not exhibit differential trends in unobserved factors that might impact changes in PSI prevalence over time. However, there might be cases in which our assumption is not valid. For example, adopting hospitals might have been simultaneously implementing other quality initiatives to improve quality of care. If this is the case, our identification would be contaminated, as we could not differentiate whether the estimated improvement in patient outcomes is driven by CPOE or by other quality initiatives.

To address these endogeneity concerns, we adopt three strategies. First, it is the case that adopting hospitals differ from non-adopting hospitals along important observable dimensions such as ownership type, size, and teaching status. While our hospital fixed effects take into account any time invariant differences between these types of hospitals, these hospitals might follow differing trends over time in both patient safety and EMR adoption. To take this into account, we have expanded our baseline model by allowing for differential trends based on teaching hospital status, ownership, and hospital size, and we find largely similar results. Our main findings are also robust to the inclusion of state-year fixed effects.[16]

Second, we run our model on a set of PSIs that are not likely to be affected by EMRs because they are mostly the result of physician skills or physical accidents. For this set of PSIs, we should not expect to find any significant effect for EMRs unless our results are driven by other quality initiatives that have been implemented simultaneously with EMR adoption. These results are reported in Table 7 for PSI6, PSI7, PSI8 and PSI15. For each of these PSIs, we find

[16] These results are available from the authors upon request.

very small and not statistically significant effects of CPOE, regardless of patient type. While some of the interaction terms are statistically significant, the overall effect of CPOE on each PSI for the less complicated groups are not statistically significant when considering the combination of the main effects and the interaction effects. It is not likely that quality initiatives would work exactly like EMRs (namely being related to our affected PSIs and not related to our unaffected PSIs). Passing these falsification tests suggests that our results are not likely driven by other quality initiatives implemented in the adopting hospitals. Note that for this falsification test, the sample is restricted to the population at potential risk for the PSIs in our main analysis (PSI9 to PSI12) so that these results are directly comparable to our main findings. Expanding the sample to all patients at risk for these placebo PSIs leads to very similar results.

[Table 7 about here]

Our third strategy for testing the parallel trends assumption is to estimate a model with the inclusion of adopting lead dummies. We define one indicator variable for being one or two years prior to adoption and one for being three or four years prior to adoption.[17] The coefficients in front of these two dummies capture whether there is any differential trend in PSI prevalence between adopting and non-adopting hospitals in the years prior to the adoption actually occurring. Column 0 of Table 8 shows that when we consider all patients together, there are no changes in PSI prevalence prior to CPOE adoption. In the subsequent columns we find no statistically significant differential pre-trends for either complicated or non-complicated cases,

[17] These are constructed by merging HIMSS adoption data from previous years to the years that we observe a hospital in the NIS data. Note that the sample size for this set of regressions is smaller since, for hospitals that have adopted CPOE prior to 2003, we are not able to track down the exact year of adoption. This applies to our following analyses of the differential effects by years since adoption too (Table 10).

regardless of our measure of complication. Results from F-tests all fail to reject that there is any significant effect of these lead dummies on less-complicated cases when considering all four years prior to adoption together. Similar to our main findings, the contemporaneous effects suggest that less complicated cases see improvements in PSI prevalence after CPOE is adopted.

[Table 8 about here]

One remaining concern is that the adoption of EMRs might be related to changes in patient composition. For example, EMR adoption may cause a different set of patients to be attracted to the adopting hospital. In addition, our results would be erroneous if EMR adoption affects the margin of patients assigned to high or low levels of complication due to changes in coding. To address these issues, we specifically explore whether patient composition changes after EMR adoption. We proceed by aggregating our data to the hospital-year level by averaging measures of patient composition, such as age, race, insurance status, and indicators for case complication. We then regress these measures on the adoption of CPOE and Physician Documentation, controlling for time and hospital fixed effects. The results are reported in Table 9. While we find a significant effect of Physician Documentation on the fraction of white patients, all the remaining coefficients are small and not statistically significant. We also find no evidence that EMR adoption is associated with changes in our measures of complication, with the lone exception being a small correlation between the fraction of less complex patients and Physician Documentation. Overall, we find there are no systematic changes in patient observed characteristics and patient case complication coinciding with EMR adoption, which reassures us of the validity of our identification assumption.

[Table 9 about here]

5.3. Timing of Effect

We also explore heterogeneity by time of EMR adoption. The adoption of a new EMR system may not immediately improve health outcomes. Healthcare providers, such as physicians, nurses, and other staff, must be trained to use new systems. It may take additional time for providers to learn how to use the new systems to optimally impact patient's health.[18] In this sense, we might see some delay in observing quality improvement. On the other hand, hospitals might have taken these delays into consideration when adopting an EMR. For example, employees might have been trained so that they can take advantage of the EMRs once these applications are installed and put to use.

Examining the timing of effect also mitigates a limitation of our data. Because the NIS is not a true panel, our baseline model treats hospitals that have adopted EMRs between observation years the same, regardless of which year they actually adopted the technology. By utilizing the HIMSS data to calculate the number of years an application has been installed, we can more precisely differentiate the relationship between actual adoption year and changes in patient safety.

Table 10 presents estimates separating the effect of adoption by the number of years CPOE has been put in use. While many of the coefficient estimates themselves are not statistically significant, when we combine the main effects and the low complication interactions, we find CPOE has a consistent impact on patient safety over time for less complicated cases. The

[18] Dranove et al. (2012) find that cost savings from EMRs in IT-intensive do not occur immediately and instead materialize 3 years after a system is put in place.

F-statistics for these combined effects are presented at the bottom of the table. For example, CPOE decreases non-complex patients' probability of experiencing at least one postoperative adverse event by 0.203 (15.1%) and 0.197 (14.7%) percentage points in years one and two, respectively. Having CPOE installed for three or more years lowers the chance of patients experiencing at least one adverse postoperative event by 0.222 (16.6%) percentage points. These results suggest that the effect of CPOE takes place beginning the first year of use and the effect persists over time.

[Table 10 about here]

5.4. Additional Levels of Heterogeneity

In addition to exploring differential effects of CPOE along various metrics of patient complication, we also estimate an extended model to allow these effects to vary by age group (elderly vs non-elderly) and case complication. These results are reported in Table 11. The first column replicates previous results of the heterogeneous effect by age group. In column 2, we also include an interaction between CPOE and a dummy for a non-complex case, and a three way interactions between CPOE, non-elderly and non-complex case. The results suggest that the largest decrease in occurrence of adverse events is realized for non-elderly and non-complex cases. In the remaining columns, we also explore commonality of DRG (column 3), mortality risk (column 4), and severity (column 5). We find consistent results that CPOE has the largest impact for non-elderly and non-complicated patients. In addition, we also see some improvement in patient outcomes for elderly but non-complicated cases.

By introducing two dimensions of complication (age and case complication), we find the largest effects for patients in the least complicated category when both dimensions are combined.

These results provide additional evidence the CPOE is likely to impact patient outcome through the channels that would have the largest impact on the least complicated cases, further suggesting clinical decision support as the most likely mechanism.

[Table 11 about here]

5.5. Two Alternative Outcomes

In addition to PSIs, we also present results using two alternative outcomes: inpatient mortality and length of stay. Mortality has been commonly used in the existing studies examining the impact of EMRs. Previously, we argued one concern about using mortality is that it is considered as an extreme outcome, so it might fail to capture improvement in patient outcomes that are not directly tied to patient death, especially for the decision support aspect of EMRs which tends to have a larger impact on less complicated cases. However, one could also argue that patient mortality might be a more relevant measure of outcome for the care coordination aspect of EMRs since the likely affected patients through this mechanism might be severely sick and at potential risk of mortality. To address this concern, we provide additional analyses using inpatient mortality as the outcome. In our data, we observe when a patient dies during their hospital stay; although, the results have to be taken cautiously as inpatient mortality does not capture death that occurs during a readmission or outside of the hospital.

The results for inpatient mortality are reported in Table 12. Consistent with previous findings, we find no effect of CPOE on inpatient mortality, regardless of patient characteristics.[19] In results that we do not report here, we also find no effect of Physician Documentation on

[19] The mean mortality rate is 0.017 with a standard deviation of 0.128 in the data. We also estimate an extended model to allow three-way interaction terms for CPOE, non-elderly and dummies for complication. We find consistent results that there is no effect of CPOE on patient mortality.

inpatient mortality. These findings provide additional support for our main findings that clinical decision support is likely the main mechanism through which EMRs impact patient outcomes in our study.

The other outcome we examine is patient length of stay (logarithm), and the results are also reported in Table 12.[20] Interestingly, we find a large decrease in length of stay (LOS) for non-complicated cases, consistent with our main findings that CPOE lowers the probability of adverse events, which themselves are likely to increase length of stay for those patients. For example, we find that CPOE lowers patient LOS by 1.2% for low mortality risk patients and 2.10% for low severity patients. We do not find statistically significant effects for complicated cases. Finding a positive effect for LOS and no effect for inpatient mortality among the same set of patients highlights the importance of using a less extreme outcome measure in capturing improvement in quality of care for less complicated cases.

[Table 12 about here]

6. Conclusion

By combining the Healthcare Information and Management Systems Society Analytics Database with the National Inpatient Sample, we test how adoption of advanced electronic medical records (CPOE and Physician Documentation) affects the incidence of patient safety indicators, and whether this effect differs across case complication. We find that CPOE decreases the prevalence of patient safety indicators that are likely to be amenable to decision

[20] In addition to providing evidence using an alternative outcome measure, length of stay has the advantage of being a continuous variable. Finding consistent results provides reassurance concerning the use of a linear probability model for modeling our discrete dependent variables – PSIs.

support functions, particularly for less complicated patients. We find little impact of Physician Documentation on these quality measures. Taken together, the fact that we find the most consistent benefits of EMR adoption when examining a technology with decision support features, outcomes likely to be sensitive to decision support, and patient populations for whom decision support is likely to be most beneficial, our results point to decision support as the most likely mechanism driving our results.

Our findings have important implications concerning the impact of EMR adoption on health outcomes. In contrast to previous large-scale studies that focus on Medicare populations, our findings suggest that younger populations may in fact be currently receiving larger benefits from EMR adoption. Our results regarding decision support complement McCullough et al. (2013)'s findings that care coordination mechanisms improve mortality rates for high severity Medicare patients with diagnoses specifically necessitating information management and care coordination. Taken together these studies suggest that different mechanisms can improve care along different metrics of quality for different patient populations.

The fact that we do not find evidence of care coordination playing a large role for the broad patient population in our study suggests that the impact of care coordination via EMRs might be currently limited to a relatively small group of patients. Such lack of evidence also suggests that further improvement in the interoperability of EMR systems and improved ability to take advantage of large amounts of data provided by EMR systems are necessary to reap their full benefits. Note that one caveat of this finding is that the outcome measures we use might fail to capture improvements in patient outcomes through care coordination. Finer data might also be needed to identify the set of patients that are more likely to be affected through this mechanism.

Our findings also contribute to the discussion of how to push EMR technologies forward by shedding light on which mechanisms are currently leading to health improvements and which patient subpopulations are most likely to be affected. While we find that decision support tools are leading to improved outcomes, further research is warranted to examine the care coordination aspects of EMRs and understand how providers can better make use of such aspects.

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Table 1: Comparison of Hospitals in Analysis Sample to All Hospitals, 2005

	Hospitals in Analysis Sample	AHA Hospitals in 29 States for which NIS includes Hospital IDs	Universe of Hospitals in AHA Data
For-Profit	.154	.144	.160
	(.361)	(.351)	(.367)
Nonprofit	.697	.673	.601
	(.460)	(.469)	(.490)
Bed Size	201.487	179.703	163.845
	(193.275)	(186.542)	(179.641)
Teaching	.088	.075	.062
	(.283)	(.263)	(.241)
Urban	.454	.415	.421
	(.498)	(.493)	(.494)
Inpatient Days	40.364	33.000	32.301
	(55.136)	(48.436)	(48.616)
%Medicare	.597	.624	.618
	(.262)	(.379)	(.330)
%Medicaid	.174	.164	.150
	(.693)	(.572)	(.449)
N	1,896	2,795	4,720

Note: Standard deviations are reported in parentheses. Inpatient days is measured in 1,000 days. Sample size for Inpatient days, %Medicare, and %Medicaid is smaller due to missing data.

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Table 2: EMR Adoption by Year

Year	CPOE	Physician Documentation
2003	0.070	-
2004	0.090	-
2005	0.165	0.182
2006	0.175	0.211
2007	0.198	0.234
2008	0.268	0.288
2009	0.304	0.391
2010	0.313	0.386

Note: This table reports the fraction of hospitals with CPOE and Physician Documentation installed by year. The sample includes all hospitals for which we have at least two observations in the merged HIMSS and NIS data.

Table 3: Summary Statistics of Patient Safety Indicators

	Postoperative PSIs					Control PSIs			
	PSI 9	**PSI 10**	**PSI 11**	**PSI 12**	**Agg PSI**	**PSI 6**	**PSI 7**	**PSI 8**	**PSI 15**
Mean (%)	0.27	0.12	1.04	1.15	1.81	0.08	0.27	0.02	1.04
S. D. (%)	5.19	3.51	10.17	10.65	13.31	2.81	5.14	1.43	10.15
N(Million)	9.06	4.24	3.38	9.08	9.10	8.18	5.57	5.86	8.51

Note: This table presents summary statistics of each PSI measure. The unit of observation is at the patient level.

Table 4: Summary Statistics for Aggregate PSI by Patient Complication

Case Complication	**non-elderly**		**non-complex**		**common DRG**		**low mortality**		**low severity**	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Mean (%)	1.49	2.21	1.34	2.36	0.86	2.28	0.53	4.02	0.22	2.82
S. D. (%)	12.13	14.72	11.49	15.17	9.23	14.92	7.23	19.65	4.66	16.55
N(Million)	5.19	3.91	4.94	4.16	3.04	6.05	5.72	3.29	3.52	5.49

Note: This table presents summary statistics of the aggregate PSI, measuring the occurrence of at least one of the postoperative PSIs, by categories of patient complication. The unit of observation is at the patient level.

Table 5: Effect of CPOE on Patient Safety

	(0)	(1)	(2)	(3)	(4)	(5)
CPOE	-.080	-.036	.016	-.033	.174*	.055
	(.080)	(.082)	(.077)	(.084)	(.097)	(.080)
CPOE*X		-.077*	-.180***	-.140***	-.402***	-.352***
		(.041)	(.043)	(.045)	(.099)	(.079)
F-stat of:						
CPOE+CPOE*X=0		1.84	3.47*	4.75**	6.32**	8.70***
X= 1 if…		Non-Elderly	Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of the aggregate PSIs on dummies indicating adoption of CPOE and its interaction with different measures for patient complication (X). All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$). All standard errors are clustered at the hospital level.

*** - p<.01, ** - p < .05, * - p < .10

Table 6: Effect of Physician Documentation on Patient Safety

	(0)	(1)	(2)	(3)	(4)	(5)
PhysDoc	-.002	.001	.015	-.033	.118	.042
	(.032)	(.041)	(.041)	(.037)	(.073)	(.046)
PhysDoc*X		-.011	-.069	-.054	-.200**	-.122*
		(.040)	(.045)	(.043)	(.095)	(.074)
Fstat of:						
PhysDoc+PhysDoc*X=0		0.08	0.87	0.95	3.69**	2.43
X= 1 if…		Non-Elderly	Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of the aggregate PSIs on dummies indicating adoption of Physician Documentation and its interaction with different measures for patient complication (X). All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$). All standard errors are clustered at the hospital level.
*** - p<.01, ** - p < .05, * - p < .10

Table 7: Falsification Test on Non-affected PSIs

	(0)	(1)	(2)	(3)	(4)	(5)
Panel: PS6						
CPOE	.003	.001	0.001	.003	.013	.008
	(.005)	(.006)	(0.006)	(.005)	(.008)	(.006)
CPOE*X		.003	0.002	-.004	-.016*	-.012**
		(.005)	(.005)	(.005)	(.009)	(.006)
F-stat of:						
CPOE+CPOE*X=0		0.68	0.60	0.04	0.32	0.88
Panel: PS7						
CPOE	-.005	-.004	.010	.000	.005	.002
	(.015)	(.013)	(.017)	(.016)	(.027)	(.017)
CPOE*X		-.002	-.028**	-.011	-.015	.018
		(.013)	(.011)	(.013)	(.049)	(.017)
F-stat of:						
CPOE+CPOE*X=0		0.13	1.29	0.64	0.49	1.08
Panel: PS8						
CPOE	-.002	.000	.000	-.002	-.003	-.003
	(-.003)	(.004)	(.003)	(.003)	(.005)	(.003)
CPOE*X		-.003	-.005*	.000	.001	.002
		(.003)	(.003)	(.003)	(.004)	(.003)
F-stat of:						
CPOE+CPOE*X=0		1.55	2.79*	0.45	0.59	0.15
Panel: PS15						
CPOE	-.014	.017	.012	-.014	.014	.008
	(.029)	(.031)	(.022)	(.031)	(.036)	(.032)
CPOE*X		-.054**	-.050**	-.020	-.045	-.058**
		(.024)	(.022)	(.037)	(.051)	(.028)
F-stat of:						
CPOE+CPOE*X=0		1.39	1.38	0.77	0.99	2.44
X= 1 if …		Non-Elderly	Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of a set of non-affected PSIs on dummies indicating adoption of CPOE and its interaction with different measures for patient complication (X). All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$). All standard errors are clustered at the hospital level.
*** - p<.01, ** - p < .05, * - p < .10

Table 8: Lead Effect of Adoption

	(0)	(1)	(2)	(3)	(4)	(5)
CPOE	-.085	-.040	.008	-.035	.188*	.056
	(.093)	(.096)	(.091)	(.098)	(.111)	(.095)
1 or 2 years prior	-.023	-.015	-.009	-.018	.042	-.002
	(.048)	(.065)	(.061)	(.055)	(.115)	(.076)
3 or 4 years prior	.013	.021	.021	.037	.042	.059
	(.065)	(.084)	(.080)	(.070)	(.115)	(.077)
CPOE*X		-.081**	-.178***	-.147***	-.435***	-.371***
		(.041)	(.044)	(.047)	(.101)	(.078)
1 or 2 years prior *X		-.016	-.028	-.006	-.101	-.055
		(.064)	(.053)	(.041)	(.149)	(.122)
3 or 4 years prior *X		-.015	.063	-.066	-.191	-.110
		(.055)	(.048)	(.057)	(.128)	(.104)
F-stat of:						
CPOE+CPOE*X=0		1.63	2.89*	4.10**	6.00**	8.55***
1/2 year lead + 1/2 year lead*X=0		0.36	0.53	0.28	0.84	0.54
3/4 year lead + 3/4 year lead*X=0		0.01	0.39	0.17	0.80	0.83
X= 1 if…		Non-Elderly	Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of the aggregate PSIs on dummies indicating adoption of CPOE and its interaction with different measures for patient complication (X), along with dummies variables for 1 or 2 years before adoption (Lead12), and 3 or 4 years before adoption (Lead34), and their interaction terms with X . All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$). All standard errors are clustered at the hospital level.
*** - p<.01, ** - p < .05, * - p < .10

Table 9: Effect of EMR Adoption on Patient Composition

	Age	Male	Medicare	Medicaid
CPOE	-.123	-.006	-.001	.002
	(.206)	(.005)	(.006)	(.003)
PhysDoc	.268	.002	.012	-.001
	(.268)	(.007)	(.008)	(.004)

	Private-Pay	Self-Pay	White	Black
CPOE	.001	-.004	-.024	.001
	(.005)	(.002)	(.017)	(.004)
PhysDoc	-.005	-.001	.050**	.003
	(.007)	(.003)	(.020)	(.004)

	Hispanic	Co morbidities	# of Patients	Non-Elder
CPOE	-.002	-.006	18.258	-.000
	(.003)	(.017)	(31.709)	(.006)
PhysDoc	-.003	.033	30.430	-.004
	(.003)	(.022)	(36.941)	(.006)

	Non-Complex	Common DRG	Low Mortality	Low Severity
CPOE	-.001	-.002	-.002	-.010
	(.007)	(.007)	(.006)	(.007)
PhysDoc	-.014**	.003	-.005	.003
	(.007)	(.007)	(.006)	(.007)

Note: Coefficient estimates are from separate hospital-year level regressions of a set of mean patient composition metrics on dummies indicating adoption of CPOE and Physician Documentation. All regressions control for hospital fixed effects and year fixed effects. All standard errors are clustered at the hospital level.
*** - p<.01, ** - p < .05, * - p < .10

Table 10: Differential Effects by Years since Adoption

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CPOE						
Year 1	-.146	-.059	-.077	-.100	.086	-.035
	(.099)	(.097)	(-.085)	(.104)	(.114)	(.095)
Year 2	-.149**	-0.078	-0.100	-.132	.055	-.008
	(.074)	(.084)	(.079)	(.080)	(.128)	(.093)
Year 3	-.148	-0.136	-.080	-.117	.022	-.041
	(.116)	(.119)	(.116)	(.121)	(.142)	(.117)
CPOE*X						
Year 1		-.147***	-.126*	-.139**	-.370***	-.289***
		(.053)	(.067)	(.062)	(.134)	(.252)
Year 2		-.118	-.097	-.052	-.328**	-.378***
		(.086)	(.081)	(.070)	(.151)	(.131)
Year 3		-.028	-.142	-.094	-.278*	-.289**
		(.056)	(.060)	(.068)	(.143)	(.115)
F-stat of CPOE+CPOE*X=0						
Year 1		3.73*	2.95*	5.54**	5.59**	5.78**
Year 2		5.06**	4.89**	5.28**	10.15***	13.76***
Year 3		1.86	3.24*	3.31*	3.86**	5.12**
X= 1 if…		Non-Seniors	Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of the aggregate PSIs on dummies indicating adoption of CPOE (including one year, 2 years, and 3 or more years since adoption) and their interactions with different measures for patient complication (X). All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$). All standard errors are clustered at the hospital level.

*** - p<.01, ** - p < .05, * - p < .10

Table 11: Additional Levels of Heterogeneity

	(1)	(2)	(3)	(4)	(5)
CPOE (a1)	-.036	-.003	.006	.097	.056
	(.082)	(.081)	(.087)	(.097)	(.086)
CPOE*Non-Elderly (a2)	-.077*	.022	-.075	.195***	-0.013
	(.041)	(.042)	(.046)	(.071)	(.048)
CPOE*X (a3)		-.092*	-.114*	-.303***	-.332***
		(.050)	(.062)	(.098)	(.093)
CPOE*Non-Elderly*X (a4)		-.112**	-0.027	-.221***	-0.005
		(.056)	(.051)	(.073)	(.051)
F-stat of:					
Complicated non-Seniors: a1+a2=0	1.84	0.06	0.63	7.03***	0.29
non-Complicated Seniors: a1+a3=0		1.06	1.71	5.01**	7.17***
Non-Complicated Non-Seniors: a1+a2+a3+a4=0		4.18**	6.59**	6.44**	8.59***
X= 1 if…		Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of the aggregate PSIs on dummies indicating adoption of CPOE, its interactions with different measures for patient complication (X) and a dummy for non-elderly. All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$), $non\_elderly * I\_year$ and $non\_elderly * X * I\_year$; All standard errors are clustered at the hospital level.
*** - p<.01, ** - p < .05, * - p < .10

Table 12: Alternative Outcomes

	(0)	(1)	(2)	(3)	(4)	(5)
Inpatient Mortality						
CPOE	.026	.036	.031	.036	.029	.029
	(.028)	(.040)	(.038)	(.032)	(.065)	(.036)
CPOE*X		-.027	-.021	-.013	-.016	-.014
		(.043)	(.037)	(.037)	(.086)	(.051)
F-stat of:						
CPOE+CPOE*X=0		0.07	0.11	0.48	0.11	0.18
Length of Stay (logarithm)						
CPOE	-.396	-.274	-.061	.094	.846	.650
	(.379)	(.435)	(-.470)	(.416)	(.689)	(.465)
CPOE*X		-.257	.321	-1.459**	-2.017***	-2.761***
		(.418)	(.509)	(.612)	(.810)	(.760)
F-stat of:						
CPOE+CPOE*X=0		1.53	0.44	5.25**	6.36**	11.78***
X= 1 if…		Non-Elderly	Non-Complex	Common-Drg	Low-Mortality	Non-Severe

Note: Coefficient estimates are from separate fixed effect linear probability regressions of inpatient mortality and length of stay on dummies indicating adoption of CPOE and its interaction with different measures for patient complication (X). All regressions control for hospital fixed effects, year fixed effects, patient characteristics, X, a group specific year fixed effects ($X * I\_year$). All standard errors are clustered at the hospital level.
*** - p<.01, ** - p < .05, * - p < .10

Appendix Table 1: Descriptions of Patient Safety Indicators

PSI #	PSI Name	Description
9	Postoperative Hemorrhage or Hematoma	Bleeding or bruising after an operation
10	Postoperative Physiological and Metabolic Derangement	Deficiency in the amount of oxygen reaching body tissues or other physiological complications
11	Postoperative Respiratory Failure	Conditions that affect breathing function or the lungs themselves
12	Postoperative Pulmonary Embolism or Deep Vein Thrombosis	Blockage of main artery of the lung or one of its branches by a substance that has travelled from elsewhere in the body or a blood clot in a deep vein
6	Iatrogenic Pneumothorax Rate	a condition in which air or gas is present in the pleural cavity as a result of mechanical ventilation, tracheostomy tube placement, or other therapeutic intervention
7	Central Venous Catheter-Related Blood Stream Infection	Blood infection arising from the tubular, flexible surgical instrument that is inserted into a cavity of the body to withdraw or introduce fluid.
8	Postoperative Hip Fracture Rate	Hip fractures after an operation when hip fracture was not present on admission excluding some cases such as muscular disorders or violent seizures where fracture may not be fault of hospital
15	Accidental Puncture or Laceration Rate	Accidental puncture or cut during procedure