Saving Patient Ryan—Can Advanced Electronic Medical Records Make Patient Care Safer?

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Patient safety is one of the foremost problems in US healthcare, affecting hundreds of thousands of patients and costing tens of billions of dollars every year. Advanced electronic medical records (EMRs) are widely expected to improve patient safety, but the evidence of advanced EMRs' impact on patient safety is inconclusive. A key challenge to evaluating EMRs' impact on safety has been the lack of reliable and comprehensive data. We overcome this challenge by constructing a panel of Pennsylvania hospitals over 2005–2012 using data from several sources. In particular, we source confidential patient safety data from the Pennsylvania Patient Safety Authority (PSA). Since mid-2004, Pennsylvania state law has mandated that hospitals report a broad range of patient safety events to the PSA. Using a differences-in-differences identification strategy, we find that advanced EMRs lead to a 27 percent decline in patient safety events. This overall decline is driven by declines in several important subcategories—30 percent decline in events due to medication errors and 25 percent decline in events due to complications. Our results hold against a number of robustness checks, including, but not limited to, falsification test with non-clinical IT and falsification test with a subcategory of events that is not expected to benefit from advanced EMRs. Overall, we provide evidence to policy makers, hospital administrators, and other stakeholders that hospitals' adoption of advanced EMRs improves patient safety.

Acknowledgements: We thank Idris Adjerid, Bernard Black, Erik Brynjolfsson, Chris Forman, John Gardner, Martin Gaynor, Avi Goldfarb, Shane Greenstein, Tat Koon Koh, Rema Padman, Michael D. Smith, Jonathan Treadwell, and Catherine Tucker for helpful suggestions. We also thank seminar participants at the National Bureau of Economic Research Summer Workshop; The Office of the National Coordinator for Health Information Technology (ONC) Summer of Data Meeting; ONC's National Health IT Week; and the Pennsylvania Patient Safety Authority Board Meeting. We are responsible for all opinions and errors.

We cannot look at insurance coverage, medical costs, quality of care and information technology as separate issues.

-Paul O'Neill, 72nd US Secretary of the Treasury (New York Times 2007).

1. Introduction

Patient safety is one of the foremost problems in US healthcare. According to the landmark Institute of Medicine (IOM)[1] report *To Err is Human: Building a Safer Health System*, 44,000 to 98,000 people die each year in US hospitals from preventable medical errors (see IOM 2000, Chap. 2). In addition, hundreds of thousands of other patients survive after being harmed or after having faced the risk of harm from medical care. Moreover, patient safety events cost tens of billions of dollars to society (Bos et al. 2011, Seabury et al. 2012, Cheeks 2013).

Health information technology (IT) is widely considered part of the solution to improving the safety of healthcare in the United States. For instance, the IOM report *Health IT and Patient Safety* notes: "One strategy the nation has turned to for safer, more effective care is the widespread use of health information technologies" (IOM 2012, p. 1). The question of interest is whether hospitals' adoption of health IT has matched expectations and improved patient safety. Despite the importance of this question to policy makers, hospital administrators, patients, and other stakeholders, the IOM concluded from a review of more than 200 research articles: "...current literature is inconclusive regarding the overall impact of health IT on patient safety" (IOM 2011, slide 22). The IOM report and other experts note that existing research on this topic suffers from limited samples (one or few prominent hospitals), weak methodology, and conflict of interest due to researchers' financial ties to the health IT industry. Furthermore, systematic reviews of the existing literature do not suggest a general pattern of impact of health IT on patient safety—with some studies suggesting a positive impact and other studies suggesting mixed or no impact. Press reports, while acknowledging the potential of health IT in improving patient safety, have highlighted unfortunate incidents such as the death of a woman and a baby boy which may have

[1] The Institute of Medicine is one of the four organizations that comprise the National Academies.

been health IT-induced (Rowland 2014). Thus, the overall impact of health IT on patient safety remains an unsettled empirical question.

We contribute to the literature on the value of health IT generally and to the question of health IT's impact on patient safety specifically by constructing a novel data set and using rigorous methods. A key challenge to evaluating IT's impact on safety has been the lack of reliable and comprehensive data. We overcome this challenge by constructing a panel of Pennsylvania hospitals over 2005–2012 using data from several sources. In particular, we source confidential patient safety data from the Pennsylvania Patient Safety Authority (PSA). Since mid-2004, Pennsylvania state law has mandated that hospitals report all patient safety events to the PSA. These data allow us to test the impact of hospitals' adoption of advanced electronic medical records (EMRs) on patient safety events while controlling for hospital fixed effects, year fixed effects, hospital size, hospital teaching status, and other hospital-level covariates (we also control for county-level covariates, including population, median household income, and unemployment). Using a differences-in-differences identification strategy, we find that advanced EMRs lead to a 27 percent decline in patient safety events. This overall decline is driven by declines in several important subcategories—30 percent decline in events due to medication errors and 25 percent decline in events due to complications.

Thus, our study offers evidence to hospital managers and policy makers of substantial improvements in patient safety due to the adoption of advanced EMRs. Despite financial incentives from the federal government, advanced EMR adoption in the US was 67 percent in 2012.[2] Our results suggest that further efforts to foster the adoption of advanced EMRs will make the resulting patient safety benefits more universal.

2. Health IT, Electronic Medical Records, and Patient Safety

Health IT is an all-encompassing term for computer and communication technologies used by healthcare providers. Although many IT applications play a role in the overall improvement of care quality and patient safety, EMRs play a particularly salient role and thus EMRs are widely studied by multiple disciplines. However, precisely defining EMRs is difficult because EMRs continue to

[2] Source: HIMSS

evolve. Table 1 lists applications that the Healthcare Information and Management Systems Society (HIMSS) deems to be part of "Electronic Medical Records" category.

Table 1 Electronic Medical Records Component Applications

Category	Applications
Electronic Medical Record	Business Intelligence - Clinical Clinical Data Repository (CDR) Clinical Decision Support System (CDSS) Computerized Practitioner Order Entry (CPOE) Order Entry (Includes Order Communications) Patient Portal Physician Documentation (PD) Physician Portal

This table lists all application components categorized by HIMSS as *Electronic Medical Records* in HIMSS dataset 2012.

Table 2 provides a synopsis of four EMR applications: Clinical Data Repository (CDR), Clinical Decision Support System (CDSS), Computerized Provider Order Entry (CPOE), and Physician Documentation (PD). Dranove et al. (2014) define *basic EMR* as CDR or CDSS and *advanced EMR* as CPOE or PD. CDR and CDSS are baseline EMR applications but may not form part of the physician workflows. In contrast, CPOE and PD are integrated into physician workflows and may also have the most clinical impact (Jha et al. 2010, p. 1952; Jha et al. 2009*b*, pp. 1634–1635). The remaining applications in Table 1 have either been supplanted (e.g. Order Entry by CPOE), are too new (e.g. Business Intelligence), or considered less consequential for patient safety. Henceforth, we primarily focus on advanced EMR applications.

2.1. Patient Safety

Great Britain House of Commons Health Committee (2009) defines patient safety as "freedom, as far as possible, from harm, or risk of harm, caused by medical management (as opposed to harm caused by the natural course of the patient's original illness or condition)." Until recently, the medical community viewed medical errors and concomitant harm either as unavoidable side effects of modern medicine or the result of medical treatment by incompetent providers. Leape (1994) argued forcefully that many errors are preventable and many are "evidence of system flaws not character flaws." The publication of *To Err is Human* (IOM 2000) catapulted the patient safety movement into the medical mainstream. The goal of the patient safety movement is to

Table 2 CDR, CDSS, CPOE, PD

Application	Description
Clinical Data Repository (CDR)	Stores real-time data about individual patients, storing data that includes patient demographics, clinical information, hospitalization history, billing, and more
Clinical Decision Support Systems (CDSS)	Assist providers in care decision by providing reference information as well as suggestions for care. CDSS generate care suggestions by applying pre-defined rules to patient data e.g. suggestions on drug-allergy contraindications for a specific patient
Computerized Provider Order Entry (CPOE)	Enables providers to electronically add, change, store, and retrieve medication orders, laboratory orders, and radiology orders and to consult with other providers
Physician Documentation (PD)	Consolidates progress notes across hospital departments and thus enables communication between care providers e.g. physicians and pharmacists. Physicians electronically record clinically relevant information in *progress notes* after each encounter with patients.

This table briefly describes the following clinical IT systems: CDR, CDSS, CPOE, and PD.

eliminate preventable patient harm through improved systems and to find solutions when harm is traditionally considered unpreventable (Wachter 2012, pp. 3, 450).

There are several different methods for identifying patient safety events, each with their own strengths and shortcomings when applied to epidemiological measurement. We briefly describe some of these methods: (I) *Voluntary or Mandatory Reporting Systems:* require care providers to report patient safety events to a common organization such as the Pennsylvania Patient Safety Authority. (II) *Patient Safety Indicators (PSIs):* are inferred from administrative billing data using an indicator set such as the 25 PSIs in the July 2010 version of AHRQ's PSIs (Wachter 2012, pp. 452-453). Although researchers can construct large nationally representative samples using PSIs, AHRQ and other experts have urged caution when using PSIs.[3] Jha and Classen (2011) write that "... poor-quality measures are plentiful. The best known among these are patient-safety indicators, which use billing data ...."[4] (III) *Global Trigger Tools (GTTs):* are sets of defined rules applied in retrospective reviews of medical records to identify "trigger" events that may indicate iatrogenic injury. Further investigation of positive triggers may be needed to determine whether an adverse event occurred. GTTs are labor-intensive, requiring review by trained analysts. GTTs may generate

[3] Please see (Isaac and Jha 2008, White et al. 2009, Romano et al. 2009) and (Wachter 2012, pp. 8, 17). [4] "Although there is a shortage of good patient-safety metrics, poor-quality measures are plentiful. The best known among these are patient-safety indicators, which use billing data to identify potential complications during a hospitalization. They generally have poor sensitivity and specificity, and their utility varies with hospitals' billing practices."

too many alerts and may miss adverse events that have not been prospectively defined. Although GTTs appear "to be sensitive in detecting adverse events", they are not extensively validated and are largely used as a research tool rather than an operational tool for monitoring safety (Jha and Classen 2011).

2.2. Mechanisms of EMR Impact on Patient Safety

Modern medicine is extremely complex. There are more than 14,000 different diagnoses (WHO 2013), more than 6,000 drugs, and more than 4,000 medical and surgical procedures (Gawande 2011). The sheer number of diagnoses, drugs, and procedures produces cognitive overload that may lead to errors by competent, caring, and conscientious care providers. As Spear and Schmidhofer (2005) state, healthcare needs to "overcome the potential for catastrophe brought on by work complexity, knowledge intensiveness, and variety and volatility of circumstance." The main mechanisms by which we may improve patient safety are by using tools that "can improve communication, make knowledge more readily accessible, require key pieces of information (such as the dose of a drug), assist with calculations, perform checks in real time, assist with monitoring, and provide decision support" (Bates and Gawande 2003). Each item in this list of mechanisms for improving patient safety requires not only well-designed IT systems but also thoughtful workflow process redesign.

However, health IT's effect on patient safety is not always beneficial, and some patient safety events may be induced by health IT. Analysis of IT-induced incidents by Magrabi et al. (2010, 2012) points to input problems, information transfer problems, output problems, technical problems, and human contributing factors as the broad categories of errors. Koppel et al. (2005) found that CPOE increased 22 types of medication error risks, although Westbrook et al. (2012) found an overall improvement in medication errors due to e-prescribing systems. In specific instances, health IT–induced errors may cause serious harm to patients (Rowland 2014) although health IT may be beneficial to patient safety on average.

2.3. Evidence for the Impact of Health IT on Patient Safety

Despite the importance of this topic, measuring the impact of various interventions (including health IT) on patient safety has been challenging (e.g., see Landrigan et al. 2010). The IOM report

Health IT and Patient Safety, while acknowledging that the US has adopted health IT with the expectation of safer care, reports that "the evidence in the literature about the impact of health IT on patient safety, as opposed to quality, is mixed" (IOM 2011, pp. 1-2) and even more explicitly "...current literature is inconclusive regarding the overall impact of health IT on patient safety" (IOM 2011, slide 22).

We summarize some of the reasons why the literature has not been able to settle this question. Since large-scale data is hard to gather, many of the studies are done at single or few sites at prominent hospitals (IOM 2011). For instance, Aron et al. (2011) use a 3-year panel from two large Asian hospitals to find that automation has a beneficial impact on medical errors. The conclusions of these small sample studies may not generalize. Though the medical informatics literature includes systematic reviews of studies performed at few sites, the conclusions of these reviews are not definitive. Measuring patient safety is another challenge. For example, some studies have measured patient safety outcomes using PSIs, which are inferred from billing data using AHRQ algorithms. With select PSIs as outcome measures, Parente and McCullough (2009) find a small beneficial effect of EMR, Freedman, Lin and Prince (2014) find beneficial effects of CPOE, Culler et al. (2007) find no effects or harmful effects of health IT, and Menachemi et al. (2007) find beneficial effects of health IT. As outlined earlier, PSIs are measures with significant limitations.

A closely related stream of research literature investigates the effects of health IT on clinical outcomes such as mortality. Miller and Tucker (2011) use county-level panel data over 1995–2006 to find that EMRs reduce neonatal mortality by 16 deaths per 100,000 live births. However, their measure is limited to infant mortality. McCullough, Parente and Town (2013) use Medicare admissions data for the years 2002–2007 to examine the role of health IT adoption on patient outcomes for four conditions—acute myocardial infarction, congestive heart failure, coronary artherosclerosis, and pneumonia. They find that health IT improves outcomes for the most severe cases but does not reduce mortality for the median patient. However, the sample was limited to Medicare patients in the fee-for-service program whose average age is 75 years.

In summary, lack of a representative data set has been a key challenge in this domain. Our paper incorporates a comprehensive health safety data set that is not limited to specific medical conditions, outcomes, hospitals, or patient populations. While our data is not without limitations, we believe it overcomes significant challenges in the current literature.

3. Data Sources and Variable Construction

We construct an unbalanced panel for Pennsylvania hospitals over 2005–2012 by collating data from multiple sources: (i) measures for patient safety are sourced from the Pennsylvania Patient Safety Authority (PSA), (ii) measures for adoption of health IT are sourced from the HIMSS data set, (iii) hospital-level controls are sourced from the Pennsylvania Health Care Cost Containment Council (PHC4) and the American Hospital Association (AHA survey data), and (iv) location-specific controls are sourced from the Area Health Resources Files (AHRF).

3.1. PSA Event Data

An independent state agency established through a legislative act, the PSA is chartered to reduce medical errors by identifying problems and proposing solutions that promote patient safety in hospitals and other healthcare facilities. To identify patient safety problems, PSA maintains the Pennsylvania Patient Safety Reporting System (PA-PSRS) as a central repository for all reported patient safety events. Since 28 June 2004, Pennsylvania hospitals have been mandated to report patient safety events through PA-PSRS. The pioneering legislation for mandatory reporting "Medical Care Availability and Reduction of Error (MCARE) Act", also known as Act 13 of 2002, was passed by the General Assembly of Pennsylvania on 20 March 2002.

MCARE promotes reporting of patient safety events by mandating that healthcare workers report serious patient safety events and infrastructure failure events within 24 hours. The healthcare worker must first report a patient safety event through an official system created by the hospital but may file an anonymous report directly to the PSA if the worker suspects that the hospital failed to report to the PSA. MCARE protects the healthcare workers by prohibiting hospitals from retaliating against the worker for reporting events, in accordance with the Whistleblower Law.

Nonetheless, the law permits hospitals to take action against workers for substandard performance, unprofessional conduct, or false reporting. Patient privacy is protected, as the event report should not include any information that can identify the patient. A hospital that fails to submit a report of a mandated event will be in violation of the Health Care Facilities Act and may be subject to an administrative penalty of $1,000 / day. MCARE assures that any patient safety event reports submitted to the PSA are confidential and are not discoverable for (or admissible as evidence in) any civil or administrative action or proceedings. While hospitals vary in their interpretations of MCARE reporting requirements, MCARE reduces disincentives for reporting of events for the stakeholders by protecting submitted information from use in medical malpractice litigation.

We use an extract of the PSA data set, which includes all events reported from 1 January 2005 to 31 December 2012. For this eight-year period, the data set has 231 unique Pennsylvania hospitals, though the number of hospitals varies by the year. These hospitals reported approximately 1.7 million events over eight calendar years, classifying 214 distinct event types in nine categories.

Table 4 provides counts of events during 2005–2012 by event categories. The five most frequent event categories are: (1) errors in procedure, treatment, or test (error PTT); (2) medication errors; (3) falls; (4) skin integrity events; and (5) complication of procedure, treatment, or test. The top two event types—medication errors, and errors related to procedure, treatment, or test—account for more than 700,000 event reports.

Table 5 provides a panel summary of patient safety events—by hospital-year, roughly 1,000 events were reported on average. Variations in reported events are higher between hospitals than within hospitals. These variation patterns may be partially explained by size and reporting culture of the hospitals. Figure 2 shows a net increasing time trend for total number of events as well as a net increasing time trend for average number of events per hospital—there were roughly 165,000 events at an average of 800 events per hospital in 2005, which increased to roughly 230,000 events at an average of approximately 1,000 events per hospital in 2012. The per-hospital average number of events dropped slightly in the years 2010 and 2011 but climbed back to exceed the earlier levels by the year 2012.

3.2. PHC4, AHA, and AHRF Data

We source hospital-level controls from the PHC4[5] data set and the AHA Annual Survey.[6] The original PHC4 data set contains 237 unique hospitals, although the number of hospital varies by year, as is the case with PSA data. For every hospital, PHC4 data provides us with unique facility ID, unique AHA ID, physical address, and quarterly inpatient days (from the first quarter of 2005 to the fourth quarter of 2012). We aggregate quarterly inpatient days to annual values and use these calculated values to measure the size of the hospitals. Using the AHA ID, we join PHC4 data with AHA data to add several hospital-level binary indicators—Joint Commission (JC) accreditation, approved residency program, medical school affiliation, and Council of Teaching Hospitals and Health Systems membership. The joined PHC4 and AHA data set contains 202 unique hospitals. The AHA data set also provides us with Medicare number, which we use to join with the HIMSS data set as described in a later section.

For location-specific controls, we use the Federal Information Processing Standards' (FIPS) county code to match records from AHRF to the combined PHC4 and AHA data. We source the following county-level variables: (i) population estimate (2002), (ii) percentage of population over 65 (2002), (iii) percentage of population belonging to white race (2002), and (iv) median household income (2000). Although it is plausible that these location-specific controls may be correlated with both EMR adoption and patient safety events, we do not expect these controls to have a major impact on the estimated effects of EMRs on patient safety. We follow the practice of earlier authors (Dranove et al. 2014) of EMR effect studies in including these location-specific controls.

[5] PHC4 is an independent state agency "formed under Pennsylvania statute (Act 89 of 1986, as amended by Act 3 of 2009) in order to address rapidly growing healthcare costs . . . The Council collects over 4.5 million inpatient hospital discharge and ambulatory/outpatient procedure records each year from hospitals and freestanding ambulatory surgery centers in Pennsylvania. This data, which includes hospital charge and treatment information as well as other financial data, is collected on a quarterly basis and is then verified by PHC4 staff. The Council also collects data from managed care plans on a voluntary basis" [Source: PHC4 Mission web page (accessed Nov. 2013)]. [6] The AHA Annual Survey provides a nearly complete census of US hospitals. AHA Annual Survey includes data "covering organizational structure, facility and service lines, inpatient and outpatient utlization, expenses, physician arrangements, staffing, corporate and purchasing affiliations, teaching status, geographic indicators, cross-reference identifiers (Medicare Provider Number and NPI)" [Source: AHA Annual Survey Database Description webpage (accessed Nov. 2013)].

3.3. HIMSS Health IT Data and the Combined Data Set

HIMSS is a not-for-profit organization with a stated mission of "optimizing health engagements and care outcomes through information technology." The HIMSS data set is a long-running national survey of US hospitals that primarily tracks health IT adoption and includes more than 3,000 hospitals for each year of our study. Although not without limitations, the HIMSS survey is the best available data source for a study of this type and is widely used in the research literature as a source of hospital IT data (Miller and Tucker 2011, Dranove et al. 2014, Parente and McCullough 2009, Freedman, Lin and Prince 2014, McCullough, Parente and Town 2013).

We use HIMSS data from the years 2005 to 2012 to construct EMR adoption measures. For most hospitals, HIMSS directly reports the status of adoption for CDR, CDSS, CPOE, and PD. We define the year of adoption of the particular EMR component as the year following the first year when a specific hospital reported a status of "live and operational." First, even when a business information system has been declared "live and operational", it may take several months to stabilize. Second, the HIMSS survey is conducted on a rolling basis throughout the year. A hospital may adopt an EMR component in the month of November and HIMSS data set may show this hospital as "live and operational" if the survey for this particular hospital is conducted in December. Clearly, the EMR component adopted in November cannot influence patient safety events in the months preceding November. Taking the hospital's adoption year as the year succeeding the hospital's declaration of "live and operational" status ensures time precedence between EMR adoption and patient safety events.

We construct our focal variables by closely following the definition provided by Dranove et al. (2014): *basic EMR* is defined as adoption of CDR or CDSS and *advanced EMR* is defined as the adoption of CPOE or PD. Table 6 summarizes relevant measures for EMR adoption in Pennsylvania, while Figure 1 plots the trend.

Our final data set is a combination of data from AHA, AHRF, HIMSS, PHC4, and PSA. A list of variables is included in Table 3. The joining of several data sets leads to loss of observations due to mismatch or missing values; this is an issue acknowledged by other health IT researchers

Table 3 Variables Used

Name	Type	Unit	Source	Description
Basic EMR	Binary	Hospital	HIMSS	Adoption of CDR or CDSS (calculated)
Advanced EMR	Binary	Hospital	HIMSS	Adoption of CPOE or PD (calculated)
Patient Days	Integer	Hospital	PHC4	Number of in-patient days
JCAHO	Binary	Hospital	AHA	Accreditation from the Joint Commission
Residency	Binary	Hospital	AHA	Residency program
Med School	Binary	Hospital	AHA	Affiliation with a medical school
Teaching	Binary	Hospital	AHA	Membership in Council of Teaching Hospitals and Health Systems
Population	Integer	County	AHRF	Population of county in 2002 where the hospital is located
Percent White	0%–100%	County	AHRF	Percent of county population in 2002 that is white (non-Hispanic)
Percent over 65	0%–100%	County	AHRF	Percent of county population in 2002 that is older than 65 years
Unemployment	0%–100%	County	AHRF	Percent of county population in 2002 that is unemployed
HH Income	Number	County	AHRF	Median household income in 2000
All Events	Number	Hospital	PSRS	All patient safety events in a given year
Med. Error	Number	Hospital	PSRS	All medication error events in a given year (excluding ADE)
ADE	Number	Hospital	PSRS	All adverse drug events in a given year
Error PTT	Number	Hospital	PSRS	All errors in procedure, treatment, or test in a given year
Complications	Number	Hospital	PSRS	All complications in procedure, treatment, or test in a given year
Skin	Number	Hospital	PSRS	All skin integrity events in a given year

This table lists variables, the type of variables, the unit of analysis at which variables are measured, the data sources, and a short description for the variable.

(e.g. Dranove et al. 2014), and our study is not unique in this aspect. Table 6 and Table 7 provide summary statistics for the final data set. The reader may notice that: (i) adoption of basic EMR has less variation compared to the adoption of advanced EMR for our sample of Pennsylvania hospitals, (ii) there is a net increasing time trend for total reported patient safety events as well as sub-types of reported patient safety events.

4. Models and Identification

We will utilize the heterogeneity in the implementation of advanced EMRs across hospitals over time to identify the effect of advanced EMRs on patient safety. Given that we have panel data, we will use the differences-in-differences (DID) estimator.

Before we formally test our model, we first provide some evidence from the data on whether advanced EMRs impact patient safety measures. If advanced EMRs have any effect, their adoption would show a decline in patient safety events. Unfortunately, plotting raw data is not very useful as over time, the number of events is increasing. Also, in general, larger hospitals have more patient safety events. Thus, we factor out confounders such as hospital size, hospital fixed effects, year fixed effects, time-interacted county controls, and time-interacted hospital controls from the reported patient safety events, and plot the average value of the residual in Figure 3. The figure

shows a sharp decline in value after advanced EMRs have been adopted. This decline suggests that advanced EMRs have a beneficial impact on patient safety events. We now test the presence of this beneficial effect more formally.

Our unit of analysis is hospital-year and we have annual data for the years 2005–2012. Our dependent variables in linear models are natural logarithm of count of patient safety events at the hospital level in a particular year. We then control for hospital size, hospital fixed effects, year fixed effects, time-interacted county controls, and time-interacted hospital controls. Our DID specification follows the general form used in the literature (Dranove et al. 2014):

$$\begin{aligned}(Log\ \#\ Patient\ Safety\ Events)_{it} = \beta_0 + \beta_1(Basic\ EMR)_{it} + \beta_2(Advanced\ EMR)_{it} + \\ \beta_3(Log\ Patient\ Days)_{it} + B_4(Hospital\ Controls)_i \times (Year) + \\ B_5(County\ Controls)_i \times (Year) + \\ (Hospital\ Fixed\ Effects)_i + (Year\ Effects)_t + \epsilon_{it} \quad (1)\end{aligned}$$

Where i denotes hospital and t denotes time (year).

Our focal variable for identification is the adoption of advanced EMR. We do not focus on basic EMR, as almost 90 percent of hospitals had already adopted basic EMR by 2005, the earliest full year of patient safety data. The key assumption that must hold for identification is that any *uncontrolled* time-varying hospital attributes that impact patient safety events are not correlated with the hospital's adoption of advanced EMR. In particular, we are assuming that after controlling for all the confounders, advanced EMR adoption by a hospital is uncorrelated with the error term in equation (1). The adoption literature suggests that most hospitals' adoption decisions are associated with hospitals' size, urban vs. rural location, and teaching vs. non-teaching status (Abraham et al. 2011, Jha et al. 2009*a*, 2010, DesRoches et al. 2012). With the controls we include in our specifications, we believe that we capture the most significant sources of variation in adoption decisions and hence our identification should be robust. However, we will perform various tests to validate this assumption. In our robustness checks, we find no evidence that lagged patient safety events are driving the adoption of advanced EMR.

To control for the size of the hospital, we use contemporaneous values of *patient days* for the hospital. Although *patient days* may be impacted by EMR adoption, the magnitude of such impact

may be relatively small, as patient flow is largely determined by exogenous factors. On the other hand, we are concerned that omitting *patient days* may bias our estimates. We also include hospital-level binary controls such as accreditation with the Joint Commission (*JC*), affiliation with a medical school (*Med. School*), presence of a residency program (*Residency*), and membership in the Council of Teaching Hospitals and Health Systems (*Teaching*). These hospital characteristics may be correlated with both patient safety and advanced EMR adoption, but they are known to remain stable over time. Since we use fixed effects models, contemporaneous values of *JC accreditation, Med. School, Residency,* and *Teaching* will be differenced out as they have very little variance over time. Therefore, we use baseline values reported by AHA for the year 2009 for these hospital-level controls and include their interaction with a linear time trend in our models (following Dranove et al. 2014). Similarly, our models include interaction terms for baseline values of county-level controls and a linear time trend. These county-level controls are county population, percentage of population over 65, percentage of population that is white, percentage of population that is unemployed, and the median household income. We are not concerned that advanced EMR will have a meaningful impact on any of these variables in the short-term such that these variables should be considered intermediate outcomes. For example, it is implausible that the adoption of advanced EMR will change the county population (in the short run), which may then affect the number of patient safety events in a hospital.

Despite this extensive set of controls, it is likely that hospitals differ on unobserved factors that impact patient safety events as well as adoption of EMR systems. The most important unobserved factors are patient safety event reporting culture and general patient safety ability of the hospital. Further, hospitals with relatively more severe case mixes and performing more complex procedures may have higher rates of patient safety events. Such hospitals may also be more likely to adopt EMR systems. As long as these unobserved factors do not vary much over time for a particular hospital, we can control for all such factors by using hospital fixed effects in our models. Finally, we include year fixed effects in all our models to control for time trends.

For inference, we almost always estimate cluster-robust standard errors with clustering on hospitals. For a few models that we use for robustness checks, we estimate observed information matrix (oim) standard errors or block-bootstrap standard errors (Cameron and Miller 2013). The block-bootstrap resamples with replacement from the original sample of clusters. Specifically, the block-bootstrap estimator randomly chooses hospitals with replacement, but includes all observations for the chosen hospital. The block-bootstrap standard errors are then equivalent to cluster-robust standard errors with clustering on hospitals. We report standard errors for main regression results only but report p-values for all regression results.

We first look at the aggregate effects on patient safety by considering the sum of all patient safety events reported by a hospital in a particular year. Next, we look at the effects on three important subcategories of patient safety events that are expected to be impacted by health IT, viz., medication errors; complications of procedure, treatment, or test; and errors in procedure, treatment, or test. Finally, we look at the effect on a subcategory—skin integrity events—that is not expected to be impacted by health IT as a validation check. The basic model would remain similar to what we outlined above.

5. Results and Discussion

First, we investigate the effect of advanced EMR on all patient safety events, aggregated across all event categories. Tables 9, 10, 11, and 12 present results from estimating variants of specification (1). While these tables present similar models, the samples used for estimation are different. The main results presented in Table 9 are estimated using the entire sample. We start with a parsimonious model in Column *A1* in which we control for hospital fixed effects, year effects, and *Log Patient Days*. We then successively add more controls such as time-interacted hospital-level controls, time-interacted county-level controls, and adoption of basic EMR in the models estimated in columns *A2*, *A3*, and *A4*. The smallest estimate of the beneficial impact of advanced EMR (24 percent decline, $p = 0.04$) is from the most parsimonious specification in column *AE1*. With more controls, the estimates of beneficial impact of advanced EMR are higher and have improved

precision . The estimates range in magnitude from 24 percent decline to 27 percent decline and are statistically significant at the 5 percent level in all specifications. The estimates on *Log Patient Days* are not statistically significant but have the expected direction i.e. an increase in patient days is associated with an increase in the number of reported patient safety events. More specifically, a 100 percent increase in patient days is correlated with an increase in number of patient safety events that ranges from 9 percent to 22 percent. The estimates of year effects[7] are not always statistically significant but always in the expected direction i.e. more recent years are associated with an increase in the number of patient safety events.

The estimates in Table 9 use a sample with advanced EMR adoption as exactly reported by HIMSS. A concern with HIMSS data is that adoption is not measured accurately so that HIMSS data occasionally reports adoption in an earlier year but no adoption in later years. However, adoption of EMRs are known to be generally sticky (de-adoptions, such as at Cedars-Sinai Hospital due to physician revolt (Kumar and Aldrich 2010, Connolly 2005), are relatively rare). In Table 10 we present estimates from a sample in which we manually update the advanced EMR adoption variable so that the first reported year and all subsequent years indicate adoption. These results are similar to the ones reported earlier.

To mitigate concerns about our main sample, we estimate our main model on different sub-samples. The estimates in Table 12 are calculated from a balanced panel constructed by dropping all hospitals that are not present for the entire study period. The estimates in Table 11 are calculated from a balanced panel constructed by dropping all hospitals that do not have basic EMR for the entire study period. The estimates of beneficial impact are even higher and have better precision when we use these balanced panels. The beneficial impact ranges from a 32 percent decline to 35 percent decline, with all estimates statistically significant at the 2 percent level. The estimates on *Log Patient Days* have negative values but are very imprecise ($p > 0.49$), so the implied correlation effects can be ignored.

[7] The entire regression table with estimates for all included variables is available from the authors.

5.1. Effect of Advanced EMR on Subcategories With Expected Benefit

Although EMR adoption and the related work process changes may have a beneficial impact on all subcategories of events, the beneficial effects are expected to be more salient on a few subcategories. We specifically look at three subcategories that produce large number of events and that are expected to be affected by the adoption of advanced EMR, viz., medication errors; error in procedure, treatment, or test; and complications of procedure, treatment, or test. By focusing on subcategories, we get two insights: (i) which subcategories benefit from advanced EMR, and (ii) which subcategories are driving the overall average beneficial effect.

5.1.1. Medication Errors The subcategory medication errors does not include adverse drug reactions but tracks events related to dose omission, extra dosage, wrong dosage, prescription delays, incorrect medication lists, unauthorized drugs, and inadequate pain management. Policy makers, healthcare management, and the research community are especially interested in medication errors, both due to the large number of medication errors and also because of expected reduction in these events from advanced EMR adoption.

In Table 13, we estimate a model similar to specification (1) but with the logged count of medication errors as the dependent variable. Some hospitals report zero medication errors in particular years, so these observations are omitted when we take a log. We report results with the sample that omits observations with zero reported medication error event. Our findings are unchanged if we modify observations by replacing zero events with one event—the estimates with the modified sample (not included in this paper) indicate slightly higher benefits ($p = 0.02$) of advanced EMR. Column *ME1*, the most parsimonious specification in Table 13, shows the smallest benefit of 28 percent decline in medication error events attributable to advanced EMR. The estimates on controls have unremarkable magnitudes and are not precise.

We briefly explain how the underlying components of advanced EMRs may improve medication safety. CPOE can improve patient safety by alleviating communication issues (legibility, drug name confusion, confusion between metric and apothecary units, specification errors e.g. trailing

zeros), shortening transmission time and completion time, enabling "correct" ordering by making it easier to integrate with patient data and CDSS (Wachter 2012, p. 211). Physician documentation may help provide more information about the patient's indications and progress during the hospital stay. A couple of examples may illustrate how CPOE and physician documentation can impact medication errors: (I) Before the adoption of CPOE, a pharmacist may receive a patient's prescription by fax. The pharmacist would then decipher the physician's handwriting and enter the order into the pharmacy computer system. Needless to say that this workflow has redundant and error-prone steps (e.g. lost faxes, inaccurate reading of physician's handwriting). After the adoption of CPOE, the pharmacist receives a properly transcribed electronic order that eliminates some redundant and error-prone steps. Moreover, the order is available almost instantaneously to the pharmacist, potentially reducing errors due to delays in administering the drug. (II) For certain prescriptions, the pharmacist may need additional information about patient indications to correctly administer the drug. For example, the anti-coagulant drug heparin may be prescribed either for treatment of clots or for prevention of clots. These indications require different routes of administration—heparin is administered intravenously for treatment of clots, whereas heparin is administered subcutaneously for prevention of clots. Before the adoption of physician documentation, a floor pharmacist may have to gain access to the patient's paper charts to determine if heparin is prescribed for prevention or treatment; this is cumbersome. For after-hour pharmacists (in a central location), though, getting access to paper charts is even more cumbersome and more likely to cause errors. With the adoption of PD, the pharmacist can now easily check physician notes to determine the correct route of administration.

5.1.2. Complications of Procedure, Treatment, or Test The subcategory "Complications of Procedure, Treatment, or Test" tracks a broad spectrum of events that are the result of unfavorable evolution of disease and attributable to hospital care. Some examples of events in this subcategory would be myocardial infarction after surgery, cardiopulmonary arrest after anesthesia, unanticipated blood transfusion after maternity, and nosocomial infections.

Table 14 estimates specification (1) for this subcategory, using log of count of complication events as the dependent variable. As with medication errors, we use a sample that allows observations with zero reported events to drop out. The results do not change if we modify observations by replacing zero reported events with one event. We estimate a parsimonious specification that includes *Log Patient Days* and hospital fixed effects and year effects as controls in Column *CE1*. We then successively add more controls such as time-interacted hospital controls, time-interacted county controls, and basic EMR in Columns *CE2*, *CE3*, and *CE4*, respectively. We find that advanced EMR leads to at least 21 percent reduction in complication events ($p = 0.02$; Table 14 Column *CE1*). The estimates on controls have unremarkable magnitudes and are mostly imprecise.

Advanced EMRs may help reduce the risk of complications through direct mechanisms such as with errors of discrepancy between emergency departments' interpretation of x-ray and EKG and final reading, as well as through less obvious mechanisms. For example, EMR may even help when no evidence-based guidelines exist as yet and consensus cannot develop among care providers on the treatment plan (Frankovich, Longhurst and Sutherland 2011). Somewhat related to this subcategory of patient safety events, McCullough, Parente and Town (2013) find that health IT adoption reduces mortality for the most complex patients. The authors argue that health IT benefits accrue primarily to patients with conditions requiring care coordination and extensive information management.

5.1.3. Error in Procedure, Treatment, or Test (Error PTT) This subcategory broadly tracks events related to surgery or invasive procedure problems such as wrong procedure, laboratory test problems such as wrong test performed, radiology test problems such as missing orders, and referral or consulting problems such as delay in scheduling. Error PTT is the most frequently reported category in our data set, but some hospitals report no events in particular years. As we use log of the counts, such observations drop out of the analysis. In Table 15, we report model estimates from two different samples: (i) Columns *PTT1* and *PTT2* report estimates from the first sample, in which we allow observations with no reported events to drop out, and (ii) Columns

PTT3 and *PTT4* report estimates from the second sample, in which we modify observations by replacing zero reported events with one reported event. In Table 15, the magnitude and statistical precision of the estimated effects of advanced EMRs changes substantially from one sample to the other, so we are wary of making strong assertions about the effects of advanced EMRs on Error PTT. If we are correct in updating zero events to one event rather than letting the observations drop out of analysis, the results in Columns *PTT3* and *PTT4* suggest a 27 percent decline in Error PTT due to advanced EMRs.

We briefly explain how EMR may directly help prevent errors in procedure, treatment, or test. For surgeries, advanced EMRs may help with accurate ordering of the right procedure and with correct identification of the patient and site. For laboratory test problems, advanced EMRs may help with correct ordering and follow-up of the right test, correct identification of patient, correct communication of test results, and specimen quality and delivery problems. With radiology and imaging test problems, advanced EMRs may help with correct ordering of the right test, correct identification of the patient, and appropriate scheduling of the test.

5.2. Effect of Advanced EMR on Events by Harm Score

Each event is also designated a harm score. Table 8 describes harm levels and provides a count of events for each harm level. For analysis, we classify events with harm numbers 1–3 as *Near Misses*, events with harm numbers 4 or 5 as *Reached Patient, No Harm*, and events with harm numbers 6–10 as *Adverse Events*. This aggregation is important, as without any aggregation, the estimates of the impact of advanced EMRs on patient safety events by harm score are imprecise. For instance, an estimate suggests an 8 percent decline in deaths due to advanced EMRs, but the estimate is imprecise ($p = 0.42$).[8] We aggregate events into near misses, reached patient events, and adverse events to potentially improve precision of the estimates.

Table 16 shows the estimated effects of advanced EMR on the aggregated categories described above. The effect of advanced EMR on events that reached patients is large in magnitude—a 28

[8] The outcome variable was restricted to logarithm of the number of reported deaths (that is, events with harm score 10). Many hospitals do not report any patient safety related deaths in particular years, and these observations drop out of analysis when we calculate logarithms. The estimate using a Poisson model with hospital and year indicators suggests a 5 percent decline in deaths, but this estimate is also imprecise ($p = 0.68$). These results are not included in this paper but are available from the authors.

percent decline—and statistically significant. The estimated effects on adverse events and near misses also suggest a decline but the standard errors for these estimates are large.

6. Robustness

We investigate the robustness of our results in several ways: (i) we include hospitals' non-clinical IT adoption as independent variables as a falsification check and as a way to control for hospital-specific time-varying attributes, (ii) we examine if lagged patient safety events predict hospitals' adoption of advanced EMRs to defend against reverse causality, (iii) we estimate the impact for a subcategory of patient safety events that is not expected to benefit from advanced EMR adoption, (iv) we test if the results are robust to additional controls such as hospitals' case mix index and hospitals' adoption of electronic patient safety reporting interface.

The identification of beneficial effects of advanced EMRs holds for the robustness checks we describe in this section.

6.1. Are Our Results Driven by Any IT System?

Our results imply that there is something unique about EMR systems that reduces errors. However, it is plausible that IT-intensive hospitals may in general be more sophisticated and have fewer patient safety errors. Furthermore, introduction of IT in a hospital may lead to organization changes that impact patient safety. We can test this assertion in our data.

Hospitals use a variety of non-clinical IT applications that are not expected to have an impact on patient safety events. In the HIMSS data set, these non-clinical applications are aggregated into categories such as General Financials, Human Resources, Revenue Cycle Management, and Supply Chain Management.

To investigate the robustness of our main results, we model hospitals' adoption of these non-clinical IT systems in two ways: (i) We estimate the association of non-clinical IT with patient safety events while excluding advanced EMR from the model. This change in the model provides a nice falsification test that the mere presence of any IT (even if it is non-clinical IT) seems to impact patient safety event, implying that EMR is just incidental IT. (ii) We re-estimate our main

model keeping advanced EMR as the focal variable but adding non-clinical IT systems as auxiliary controls. Non-clinical IT systems provide potential control for unobserved time-varying factors (such as changes in organization or organizational culture attributable to the presence of IT) even if they do not directly affect patient safety events. In short, non-IT systems act as an instrument for some time-varying unobserved factors.

Table 21 shows the estimates for models in which we include the adoption of non-clinical IT systems as independent variables. In Column *RC1*, we exclude advanced EMRs from the model but include each of the above-listed non-clinical IT categories separately and estimate their impact on patient safety events. We measure non-clinical IT systems adoption by counting the number of underlying applications adopted by the hospital in a given year.[9] The estimated effects of these non-clinical systems are imprecise ($p > 0.30$) and are relatively small in magnitude compared to the main result on the effect of advanced EMRs. Thus, we do not find any evidence of spurious effects that may challenge our main results. Next, we re-estimate the effect of advanced EMR by retaining it as the focal variable but adding non-clinical IT systems as auxiliary controls. These results, presented in Table 21 Column *RC2*, suggest that advanced EMRs lead to a statistically significant decline of 26 percent in patient safety events. The coefficient estimates and standard errors are similar to those presented as our main results in Table 9. The coefficients for the auxiliary controls—non-clinical IT systems—have small magnitudes and are imprecise ($p > 0.30$). In Column *RC3* and *RC4*, we re-estimate the models but instead of measuring the adoption of individual non-clinical IT categories as in Columns *RC1* and *RC2*, we measure adoption of non-clinical IT as an aggregated variable. The coefficient estimates for the aggregated non-clinical IT variable are small in magnitude and imprecise ($p = 0.13$), as given in Column *RC3*, whereas the adoption of advanced EMRs leads to 26 percent decline in patient safety events, as given in Column *RC4*.

To summarize: (i) we find no evidence that non-clinical IT systems spuriously impact patient safety events due to any unobserved time-varying hospital attribute (Columns *RC1* and *RC3*),

[9] The results are very similar if we measure adoption of non-clinical IT systems as binary variables rather than count variables.

and (ii) advanced EMR adoption leads to a 26 percent decline in patient safety events when we add non-clinical IT systems as auxiliary controls (Columns *RC2* and *RC4*).

6.2. Is Adoption Driven by Patient Safety Events?

A plausible concern could be that hospital management may adopt advanced EMR as a palliative measure if the number of patient safety events at the hospitals are high (and/or rising). Although anecdotes from healthcare workers suggest otherwise, our identification strategy for the effect of advanced EMR becomes questionable if patient safety events were indeed driving the adoption decisions such that hospitals are adopting advanced EMRs when the number of patient safety events are close to their highest.[10] To defend against this threat to identification from reverse causality, we investigate if lagged patient safety events in our sample of hospitals predict the adoption of advanced EMRs. We use three different tests for our checks: (i) we test if there are any non-zero anticipation effects of the adoption of advanced EMRs using lead values of advanced EMR adoption, (ii) we model the adoption decision as a binary choice process and estimate a logistic regression model with hospital fixed effects, and (iii) we model the time to adoption using a Cox proportional hazards regression model. As is well known, the underlying assumptions and interpretation of results differ for logistic regression models and Cox proportional hazards regression models. In this paper, we do not investigate the underlying assumptions to ascertain which model may be more appropriate for our problem. Instead, we present the results from both these models and note that the model estimates agree in their implications, i.e., we do not find any statistically significant evidence that lagged patient safety events or changes in lagged patient safety events predict the adoption of advanced EMRs in our data set.

First, we model hospitals' adoption of advanced EMRs as a binary decision process. Table 17 presents estimates from a binary logit regression model with hospital fixed effects in which we investigate whether (two-year) lagged patient safety events and (two-year) lagged patient days

[10] For proper identification in this case, we will need to include both fixed effects as well as lagged dependent variables. As Joshua D. Angrist and Jorn-Steffen Pischke (2008) discuss on pp. 243–247, we will need very strong assumptions for consistent estimation if we include both fixed effects and lagged dependent variables so we do not estimate this model. On the other hand, we find support for our main results from lagged dependent variable (only) models, although we do not present those results in this paper. We find that estimates are directionally consistent for lagged dependent variable (only) models and fixed effects (only) models.

predict the adoption of advanced EMRs. We also investigate whether the annual change in patient safety events predicts the adoption of advanced EMRs. This investigation is to address the concern that hospitals' decision to adopt advanced EMRs may be predicted by annual changes in patient safety events rather than absolute count of events e.g. hospital management may see a sudden rise in patient safety events and decide to adopt advanced EMRs. We use two-year lags as the deployment of advanced EMRs takes time after a decision has been made. The estimates are not statistically significantly different from zero. Next, we further confirm that lagged values of patient safety events are not driving advanced EMRs adoption, by investigating if time to adoption[11] is impacted by lagged patient safety events using a Cox proportional hazards regression model. Our data is right censored—Table 6 shows that at the end of year 2012, only 69 percent of the hospitals have adopted advanced EMRs (and the remaining hospitals have *survived* the adoption of advanced EMRs). Table 18 presents the results of the proportional hazard rate model. We investigate if two-year and three-year lagged events, controlled for lagged patient days, predict the time to adoption. Again, the estimates are not statistically significantly different from zero.[12] Finally, we test if there are any anticipation effects for the adoption of advanced EMRs by estimating a model with lead values of advanced EMR adoption. Table 19 shows that the estimates on lead value of advanced EMR adoption have relatively small positive magnitudes and very large standard errors ($p > 0.40$). These estimated anticipation effects, statistically not different from zero, provide further evidence against any threat to identification through reverse causality.

In summary, the results from these models do not provide any evidence that lagged patient safety events are endogenously driving adoption decisions at particular hospitals.

6.3. Does Advanced EMR Affect a Subcategory With No Expected Benefits?

For further validation, we focus on an event type subcategory—skin integrity—for which very little direct benefit from the adoption of advanced EMRs is expected. Skin integrity events include

[11] The underlying dependent variable is a latent hazard rate. [12] For both these models, we do not discuss the change in the odds ratio or the relative hazard associated with changes in patient safety events. First, the estimates are not statistically significant. Second, we are treating our predictor variables—patient safety events —as continuous variables and constructing good illustrative interpretation would be too lengthy for a subsection for robustness check.

pressure ulcers, venous stasis ulcers, burns, rashes, hives, abrasions, lacerations, blisters, and skin tears. These events are caused by problems with patient positioning, movement, or manipulation; physical environment; or use of devices near or on patients. Based on conversations with patient safety workers and medical providers, we do not expect this subcategory to be directly impacted by the adoption of advanced EMRs. Table 20 summarizes the results for skin integrity events for specification (1), but with log of count of skin integrity events as the dependent variable. We estimate specification (1) on two different samples—first, in which we let observations with zero reported events drop out, and second, in which we change observations by replacing zero reported events with one reported event. In all the models, the impact on skin integrity patient safety events have relatively smaller magnitudes—1 percent increase to 7 percent decrease. Moreover, the estimates are not statistically significant, with $p > 0.49$. The lack of evidence of an effect on skin integrity patient safety events further strengthens our main results.

6.4. Are Results Robust to Additional Controls

In our main analysis, we assume that hospitals' case mix is controlled through hospital fixed effects. To mitigate concerns about the effect of within-hospital variation in case mix over the study period, we check the robustness of our results by explicitly controlling for the hospital's transfer-adjusted case mix index (CMI). The CMI data is reported by the Centers for Medicaid and Medicare Services and is archived for the study period at the National Bureau of Economic Research (NBER 2014). We include CMI controls as a robustness check (cf. control in all models) as merging CMI data results in loss of observations. Another source of variation that may not be captured by hospital fixed effects is hospitals' adoption of electronic reporting to the PSA. Anecdotally, the electronic reporting interface reduces paperwork and makes it easier for hospitals to report patient safety events.

Table 22 shows the estimated effect of advanced EMRs on patient safety events with the aforementioned additional controls. Although the effects have smaller magnitudes compared to our main results, the beneficial impact is still large and statistically significant. Table 23 shows the results

with these additional controls for our placebo outcome viz. skin integrity events. The estimated effects on our placebo outcomes are still statistically not different from no effect.

7. Conclusion

Using panel data from Pennsylvania hospitals over 2005–2012, we identify the impact of advanced EMRs on patient safety using a differences-in-differences identification strategy. We regress logged count of patient safety events on hospitals' adoption of advanced EMRs while controlling for hospital fixed effects, year fixed effects, hospital size, hospital teaching status, and other hospital-level covariates; we also control for county-level covariates, including population, median household income, and unemployment.

We find that the hospitals' adoption of advanced EMRs has a beneficial impact on patient safety, as reported events decline by 27 percent. This overall decline is driven by declines in several important subcategories—30 percent decline in events due to medication errors and 25 percent decline in events due to complications. We also find suggestive evidence of a decline in the most frequent subcategory of events, those due to errors in procedure, treatment, or test. We validate our results against several robustness checks. For instance, we validate that our results are not driven by reverse causality, as we do not find that lagged patient safety events can predict hospitals' adoption decisions or hospitals' time to adoption for advanced EMRs.

In this paper, our focus was to determine the effect of advanced EMRs on patient safety. A question of interest would be to estimate the economic costs and benefits of advanced EMRs with respect to improvements in patient safety. The Office of Management and Budget (OMB 2003), while acknowledging that both benefit-cost analysis (BCA) and cost-effectiveness analysis provide systematic frameworks for evaluating alternatives, encourages the use of BCA for health and safety issues. BCA requires monetizing of health benefits, which will be difficult to do incidentally as our data includes patients of all ages, all disease types, and a broad range of patient safety events. We intend to conduct this BCA separately in future work.

A limitation of our work is that we model advanced EMR as an atomic treatment and try to estimate its effects. We acknowledge that advanced EMRs are highly complex objects with

several sub-modules that may have been customized for a particular hospital environment and interconnected in idiosyncratic ways. However, our study contributes to the literature because (a) the question of the impact of advanced EMRs at this coarse level of analysis is not yet settled, (b) the construction of a valid study at a finer level of analysis will be exceedingly difficult if not impossible precisely due to the complexity and idiosyncrasy of the individual EMR implementation (admittedly though, it would be managerially more useful).[13]

Our findings should be interesting to both hospital managers and policy makers. First, advanced EMR adoption in the US was 67 percent in 2012,[14] largely driven by factors[15] such as revenue capture, cost savings, and government incentives for adoption of health IT. As our study shows, improvement in patient safety is an additional benefit of advanced EMR adoption that non-adopting hospitals should take into account when evaluating IT investments. Policy makers, who expected improvement in patient safety due to EMRs, may find validation for their expectations. Although we do not separate out patient safety events, to focus on new events introduced by health IT or historically existing errors exacerbated by health IT, we find in aggregate counts that there is an overall improvement in patient safety from the adoption of advanced EMRs.

Too many patient safety events occur in hospitals, and too many patients are placed at risk of harm unnecessarily. There is consensus among clinicians, healthcare managers, policy makers, and other stakeholders that this status quo is untenable. Technology may not be a panacea for healthcare's myriad problems, but for patient safety events in Pennsylvania hospitals, we find that advanced EMRs have a substantial beneficial effect. Further efforts in fostering adoption and meaningful use of EMRs may make the benefits more universal and help in saving patients from the risk of harm in hospitals.

[13] An analogy may be useful here: although it is toxin produced by bacteria that causes disease, it was useful to know at a coarser level initially that bacteria cause disease. The inspiration for this analogy comes from Holland (1986, p. 959), although Holland makes a different point with an example on bacteria and disease—the problem with backward search for causes of observed effects in theoretical analysis. [14] Source: HIMSS [15] These factors are not included in our study, as they are not correlated with patient safety events.

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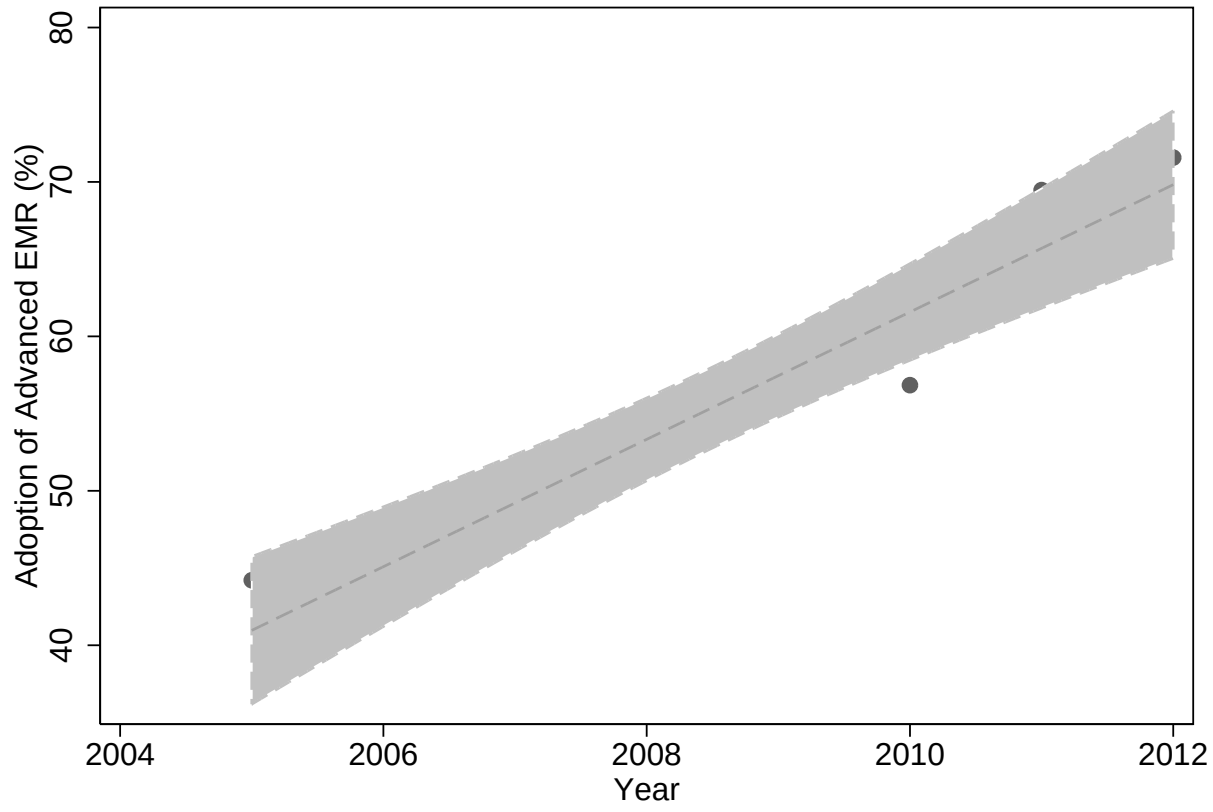
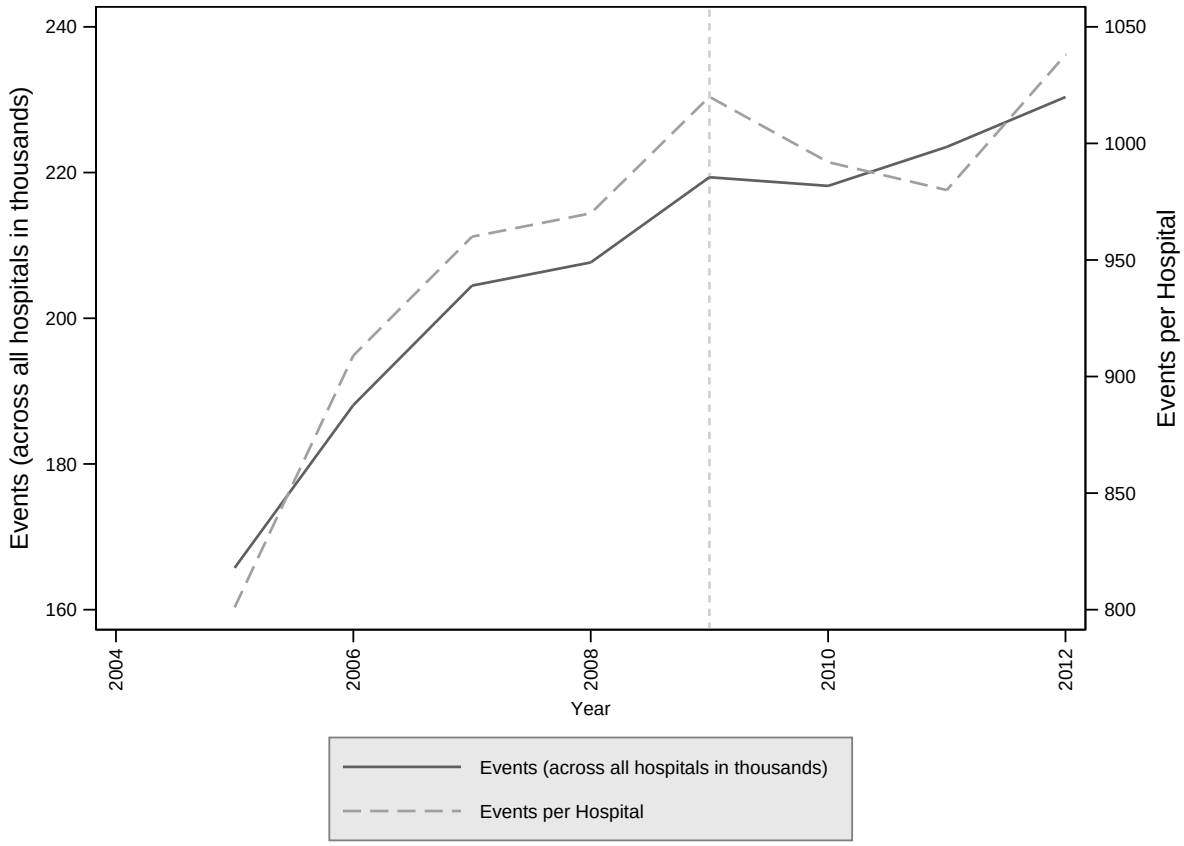
Appendices

Figure 1 Adoption Trend for Advanced EMR at PA Hospitals



This figure shows an upward trend for advanced EMR adoption at Pennsylvania hospitals during the period 2005–2012.

Figure 2 Number of Events Over Time



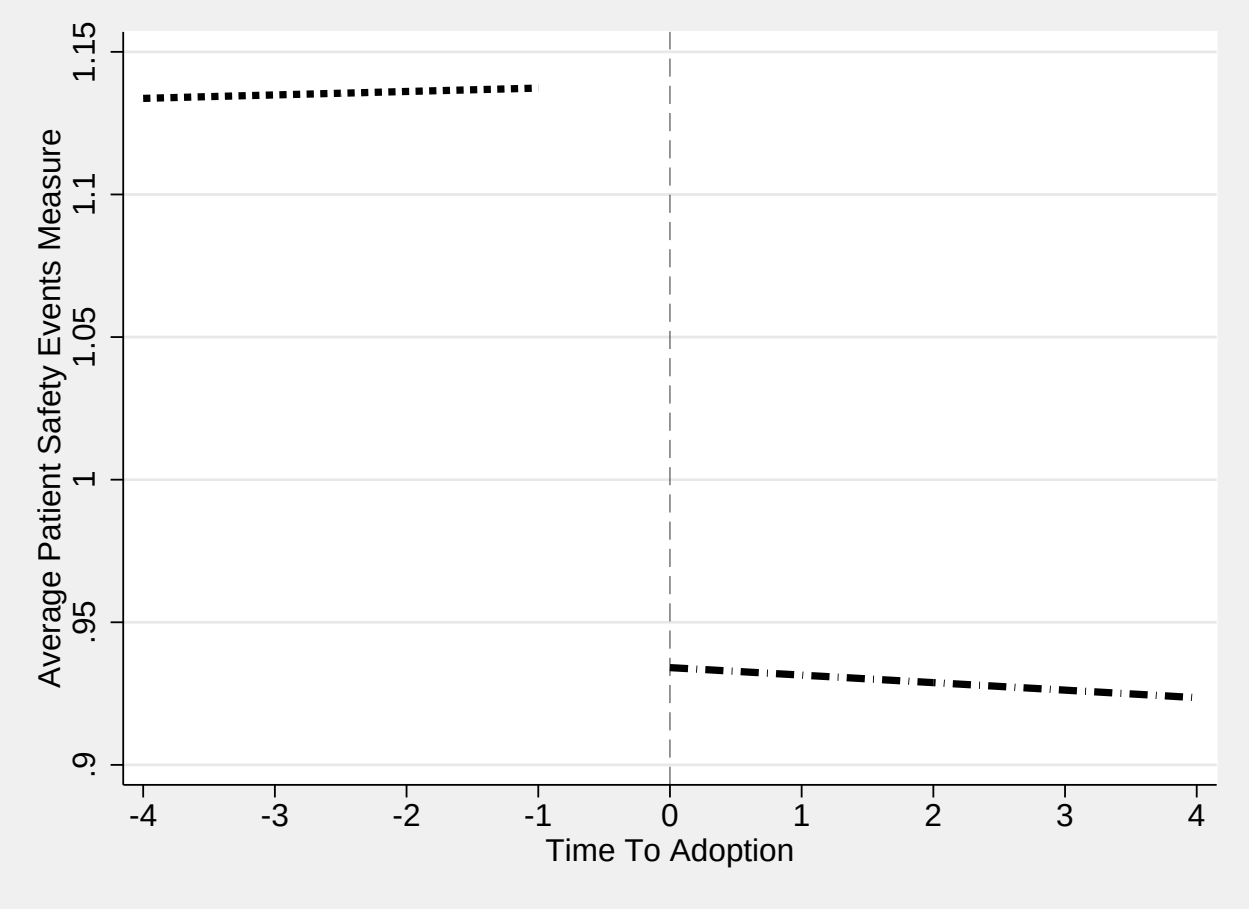
This figure shows an upward time trend for number of patient safety events and average number of events per hospitals for Pennsylvania hospitals during the period 2005–2012. The dashed vertical line is for the year 2009.

Table 4 Count of Patient Safety Events By Event Types

Event Type	Number of Reported Events
A. Medication Error	359,858
B. Adverse Drug Reaction (Not A Medication Error)	34,200
C. Equipment / Supplies / Devices	27,728
D. Fall	273,275
E. Error Related To Procedure / Treatment / Test	373,850
F. Complication Of Procedure / Treatment / Test	221,811
G. Transfusion	21,548
H. Skin Integrity	227,449
I. Other / Miscellaneous	117,659

This table presents the count of patient safety events by event types as reported by hospitals to the Pennsylvania Patient Safety Authority during the years 2005–2012. The two most frequently reported error types are medication error and error related to procedure, treatment, or test.

Figure 3 Average Patient Safety Events Measure Before and After Advanced EMR Adoption.



This figure shows the average patient safety events measure before and after advanced EMR adoption in Pennsylvania hospitals. The average patient safety events measure is calculated by factoring out the effect of hospital size, hospital fixed effects, year fixed effects, time-interacted hospital controls, and time-interacted county controls from reported patient safety events.

Table 5 Panel Summary of Reported Patient Safety Events (by Hospital and Year)

Event Type	Notes	Mean	SD	Min	Max	Obs.
# All Events	overall	960	1,337	1	10,698	1,727
	between		1,220	2	7,880	231
	within		498			
Medication Events	overall	208	399	0	5,914	1,727
	between		333	0	3,278	231
	within		207			
Skin Integrity Events	overall	132	282	0	2,508	1,727
	between		248	0	1,864	231
	within		122			
Procedure Error Events	overall	216	445	0	5,604	1,727
	between		381	0	2,212	231
	within		215			
Procedure Complication Events	overall	128	238	0	2,251	1,727
	between		206	0	1,411	231
	within		111			

This table provides a panel summary for events reported by hospital to the Pennsylvania Patient Safety Authority during years 2005–2012. Column *Mean* provides the average across all observations. Columns *SD*, *Min*, *Max*, and *Obs.* provide the standard deviation, minimum, maximum, and number of observations, respectively, which need to be interpreted based on the value in the column *Notes*. In the *Notes* column, *overall* means that the row provides statistics at the hospital-year level; *between* means that the row provides statistics for hospital means i.e. average number of events reported by hospitals across years; and *within* means that the row provides measures of variation within hospitals by providing standard deviation for demeaned hospital observations. Where applicable, numbers are rounded to integers.

Table 6 EMR Adoption for Sample of Pennsylvania Hospitals (by Year)

Year	Number of Hospitals	Basic EMR (%)	Advanced EMR (%)	CDR (%)	CDSS (%)	CPOE (%)	Physician Doc. (%)
2005	114	89	41	76	72	28	25
2006	124	87	41	75	67	28	23
2007	131	86	43	82	66	30	29
2008	138	91	47	84	78	35	35
2009	154	99	47	94	92	36	33
2010	156	100	50	94	94	39	36
2011	163	98	61	96	93	53	47
2012	163	99	69	97	95	64	53

This table presents percent EMR adoption (by year) for our sample of Pennsylvania hospitals. We lose some observations from the Pennsylvania Patient Safety Authority sample while merging data with HIMSS, PHC4, and AHRF. Percentages are rounded to integers.

Table 7 Patient Days and Patient Safety Incidents for Sample of Pennsylvania Hospitals

Year	Patient Days (millions)	All Events	A: Med Err.	E: Error PTT	F: Complication	H: Skin
2005	6.8	127,771	32,294	31,179	16,585	9,707
2006	7.1	159,546	37,319	41,866	22,875	15,795
2007	7.0	165,930	39,289	42,072	23,360	16,243
2008	7.5	184,318	40,133	45,116	22,524	25,823
2009	7.7	201,911	42,645	49,125	25,259	31,278
2010	7.5	201,446	39,093	47,720	26,030	32,163
2011	7.5	206,994	40,190	46,641	30,005	32,408
2012	7.0	208,696	41,114	48,146	31,599	30,058

This table summarizes patient days and patient safety events by year for our sample of Pennsylvania hospitals. We lose some observations from the Pennsylvania Patient Safety Authority sample while merging data with HIMSS, PHC4, and AHRF. Please see Table 4 for short description of event types in the last four columns. Column *Patient Days*, in millions, was rounded to the first decimal place.

Table 8 Count of Patient Safety Events By Harm Number (and Harm Score)

HN	HS	Num. Events	HS Type	HS Description
1	A	175,852	Unsafe Conditions	Circumstances that could cause adverse events (e.g., look-alike medications, confusing equipment, etc.)
2	B1	24,040	Event, No Harm	An event occurred but it did not reach the individual ("near miss" or "close call") because of chance alone.
3	B2	183,996	Event, No Harm	An event occurred but it did not reach the individual ("near miss" or "close call") because of active recovery efforts by caregivers.
4	C	685,356	Event, No Harm	An event occurred that reached the individual but did not cause harm and did not require increased monitoring (an error of omission such as a missed medication dose does reach the individual).
5	D	536,404	Event, No Harm	An event occurred that required monitoring to confirm that it resulted in no harm and/orrequired intervention to prevent harm.
6	E	36,799	Event, Harm	An event occurred that contributed to or resulted in temporary harm and required treatment or intervention.
7	F	10,666	Event, Harm	An event occurred that contributed to or resulted in temporary harm and required initial or prolonged hospitalization.
8	G	522	Event, Harm	An event occurred that contributed to or resulted in permanent harm.
9	H	1,198	Event, Harm	An event occurred that resulted in a near-death event (e.g., required ICU care or other intervention necessary to sustain life).
10	I	2,545	Event, Death	An event occurred that contributed to or resulted in death.

HN and *HS* abbreviate Harm Number and Harm Score, respectively. *Num. Events* abbreviates Number of Events.
Source: Harm Score type and description adapted from the National Coordinating Council for Medication Error Reporting and Prevention.

Table 9 EMR Adoption and All Patient Safety Events

	A1 b/se/p	A2 b/se/p	A3 b/se/p	A4 b/se/p
Advanced EMR	-0.242**	-0.276**	-0.267**	-0.271**
	(0.122)	(0.119)	(0.113)	(0.112)
	0.048	0.021	0.019	0.017
Log Patient Days	0.227	0.130	0.109	0.090
	(0.223)	(0.216)	(0.206)	(0.205)
	0.310	0.547	0.598	0.660
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	No	Yes	Yes	Yes
Time-Interacted County Controls	No	No	Yes	Yes
Basic EMR Control	No	No	No	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	952	952	952	952

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. *b/se/p* abbreviates estimated coefficient, standard error, and p-value respectively. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10 EMR Adoption and All Patient Safety Events (With Correction for Advanced EMR Adoption)

	A5 b/p	A6 b/p	A7 b/p	A8 b/p
Advanced EMR	-0.239**	-0.282**	-0.269**	-0.293**
	0.028	0.015	0.024	0.018
Log Patient Days	0.211	0.114	0.094	0.074
	0.337	0.595	0.647	0.716
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	No	Yes	Yes	Yes
Time-Interacted County Controls	No	No	Yes	Yes
Basic EMR Control	No	No	No	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	952	952	952	952

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. Advanced EMR adoption data in this sample has been corrected so that any hospital that adopts advanced EMR in a year remains adopted in subsequent years. This data correction changes roughly 10% of observations. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11 EMR Adoption and All Patient Safety Events (Hospitals with Basic EMR Throughout Study)

	AE1b b/p	AE2b b/p
Advanced EMR	-0.348**	-0.330**
	0.020	0.022
Log Patient Days	-0.196	-0.199
	0.526	0.492
Hospital and Year Fixed Effects	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes
Time-Interacted County Controls	No	Yes
Variance-Covariance Estimator	cluster	cluster
Observations	560	560

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. The sample is restricted to hospitals that reported basic EMR throughout the study period (hence no control for basic EMR). *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12 EMR Adoption and All Patient Safety Events (Balanced Panel)

	AE1a b/p	AE2a b/p
Advanced EMR	-0.356***	-0.353***
	0.009	0.009
Log Patient Days	-0.181	-0.195
	0.531	0.497
Hospital and Year Fixed Effects	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes
Time-Interacted County Controls	Yes	Yes
Basic EMR Control	No	Yes
Variance-Covariance Estimator	cluster	cluster
Observations	665	665

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. The sample is restricted to hospitals that have observations for all years. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13 EMR Adoption and Medication Events

	ME1 b/p	ME2 b/p	ME3 b/p	ME4 b/p
Advanced EMR	-0.285**	-0.314**	-0.294**	-0.298**
	0.020	0.010	0.013	0.011
Log Patient Days	0.255	0.221	0.201	0.186
	0.238	0.311	0.319	0.356
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	No	Yes	Yes	Yes
Time-Interacted County Controls	No	No	Yes	Yes
Basic EMR Control	No	No	No	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	932	932	932	932

The unit of analysis is hospital-year. The dependent variable is natural log of the count of medication patient safety events. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14 EMR Adoption and Complication in Procedure, Test, or Treatment

	CE1 b/p	CE2 b/p	CE3 b/p	CE4 b/p
Advanced EMR	-0.218**	-0.234**	-0.244**	-0.249**
	0.016	0.012	0.014	0.012
Log Patient Days	0.217	0.163	0.169	0.158
	0.353	0.492	0.478	0.507
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	No	Yes	Yes	Yes
Time-Interacted County Controls	No	No	Yes	Yes
Basic EMR Control	No	No	No	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	935	935	935	935

The unit of analysis is hospital-year. The dependent variable is natural log of the count of "complication in procedure, treatment, or test" patient safety events. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 15 EMR Adoption and Error in Procedure, Test, or Treatment

	PTT1 b/p	PTT2 b/p	PTT3 b/p	PTT4 b/p
Advanced EMR	-0.154	-0.163	-0.276**	-0.284**
	0.155	0.132	0.034	0.026
Log Patient Days	-0.005	-0.027	-0.066	-0.098
	0.986	0.924	0.790	0.692
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes	Yes
Basic EMR Control	No	Yes	No	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	908	908	952	952

The unit of analysis is hospital-year. The dependent variable is natural log of the count of "error in procedure, treatment, or test" patient safety events. The sample used for columns PTT3 and PTT4 has been changed by replacing observations with zero events with one event (without this change, observations with zero events drop out of analysis, as in columns PTT1 and PTT2, when we take natural logarithm). *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 16 EMR Adoption and All Events, Near Misses, Adverse Events, Reached Patients

	Adverse b/p	Near b/p	Reached b/p
Advanced EMR	-0.058	-0.138	-0.284**
	0.478	0.364	0.013
Log Patient Days	0.338	0.097	0.114
	0.272	0.721	0.585
Hospital and Year Fixed Effects	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes
Basic EMR Control	Yes	Yes	Yes
Variance-Covariance Estimator	cluster	cluster	cluster
Observations	940	909	946

The unit of analysis is hospital-year. The dependent variable is the natural log of the count of adverse events; near misses; and reached patients, no harm. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 17 Lagged All Patient Safety Events and EMR Adoption

	BLPM1 b/se/p	BLPM2 b/se/p	BLPM3 b/se/p	BLPM4 b/se/p	BLPM5 b/se/p	BLPM6 b/se/p	BLPM7 b/se/p
Lag(2) Patient Days	-0.0003	-0.0003	-0.0013	-0.0013			
	(0.4096)	(0.4835)	(0.0208)	(0.0210)			
	0.9995	0.9996	0.9501	0.9505			
Lag(2) All Events	0.0034	0.0034	0.0056	0.0056			
	(0.8405)	(2.2266)	(0.6102)	(0.5657)			
	0.9968	0.9988	0.9927	0.9921			
Lag(2) Δ All Events					-0.0009	-0.0009	-0.0009
					(1.1481)	(8.4841)	(0.0009)
					0.9994	0.9999	0.3097
Lag(3) Δ All Events							-0.0010
							(0.0014)
							0.4524
Variance-Covariance Estimator	bootstrap	bootstrap	bootstrap	bootstrap	bootstrap	bootstrap	oim
Replications	1000	1000	1000	1000	1000	1000	
Seed	11	739397	11	739397	11	739397	
Observations	144	144	89	89	89	89	48

The unit of analysis is hospital-year. The dependent variables for the models are binary indicators for adoption of advanced EMR at a particular hospital. We drop all years subsequent to the first year of adoption by a hospital. We use panel binary logit models with hospital fixed effects. *b/se/p* abbreviates estimated coefficient, standard error, and p-value, respectively. Standard errors are estimated using the observed information matrix (oim) or the block-bootstrap variance-covariance estimators. Table rows *Replications* and *Seed* specify the number of replications and seed used for bootstrap estimates of standard errors. The same model is run twice with different seeds to confirm that bootstrap estimates do not change substantially. Significance levels are: $*\, p < 0.1$ $**\, p < 0.05$ $***\, p < 0.01$.

Table 18 Lagged All Patient Safety Events and EMR Adoption (Cox Proportional Hazard Rate)

	COX1 b/se/p	COX2 b/se/p	COX3 b/se/p	COX4 b/se/p
Lag(2) All Events	0.0000	0.0004		0.0003
	(0.0001)	(0.0004)		(0.0004)
	0.8501	0.3890		0.5110
Lag(3) All Events		-0.0002	0.0002	-0.0001
		(0.0005)	(0.0002)	(0.0005)
		0.6567	0.3105	0.8404
Lag(2) Patient Days	0.0000*	0.0000		0.0001
	(0.0000)	(0.0000)		(0.0001)
	0.0820	0.5564		0.3694
Lag(3) Patient Days			0.0000	-0.0001
			(0.0000)	(0.0001)
			0.4621	0.3869
Variance-Covariance Estimator	oim	oim	oim	oim
Observations	102	87	87	87

The unit of analysis is hospital. The outcome of interest is time to adoption of advanced EMR at particular hospital, although the latent dependent variable is hazard rate. We do not know the time to adoption for hospitals that never adopt during the years 2005–2012, so the survival model adjusts for censoring of the outcome variable. The reported estimates are hazard ratios, i.e., exponentiated coefficients. *b/se/p* abbreviates estimated coefficient, standard error, and p-value, respectively. Standard errors are estimated using observed information matrix (oim). Significance levels are: $*p<0.1$ $**p<0.05$ $***p<0.01$.

Table 19 Lead(1) EMR Adoption and All Events (Anticipation Effect Test)

	A1 b/p	A2 b/p
Lead(1) Advanced EMR	0.053	0.055
	0.429	0.411
Log Patient Days	0.977***	0.975***
	0.000	0.000
Hospital and Year Fixed Effects	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes
Time-Interacted County Controls	Yes	Yes
Basic EMR Control	No	Yes
Variance-Covariance Estimator	cluster	cluster
Observations	499	499

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 20 EMR Adoption and Skin Integrity Events (Placebo Outcome)

	SE1 b/p	SE2 b/p	SE3 b/p	SE4 b/p
Advanced EMR	0.014	0.014	-0.077	-0.078
	0.869	0.869	0.503	0.496
Log Patient Days	0.117	0.117	0.207	0.203
	0.688	0.688	0.444	0.451
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes	Yes
Basic EMR Control	No	Yes	No	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	902	902	952	952

The unit of analysis is hospital-year. The dependent variable is natural log of the count of skin integrity patient safety events. The sample used for columns SE3 and SE4 has been changed by replacing observations with zero events with one event (without this change, observations with zero events drop out of analysis, as in columns SE1 and SE2, when we take natural logarithm). *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 21 Non-Clinical IT and Patient Safety Events

	RC1 b/p	RC2 b/p	RC3 b/p	RC4 b/p
Advanced EMR		-0.261**		-0.264**
		0.025		0.021
Non-Clinical IT (Lumped)			-0.022	-0.021
			0.133	0.146
General Financials	-0.078	-0.075		
	0.334	0.369		
Financial Decision Support	-0.024	-0.027		
	0.569	0.527		
Human Resources	0.023	0.008		
	0.613	0.862		
Supply Chain Management	-0.099	-0.086		
	0.303	0.370		
Revenue Cycle Management	-0.012	-0.004		
	0.666	0.888		
Log Patient Days	0.114	0.122	0.083	0.101
	0.581	0.557	0.691	0.631
Hospital and Year Fixed Effects	Yes	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes	Yes
Variance-Covariance Estimator	cluster	cluster	cluster	cluster
Observations	951	951	951	951

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 22 EMR Adoption and All Patient Safety Events (With Additional Controls)

	A1 b/p
Advanced EMR	-0.182**
	0.036
Log Patient Days	0.038
	0.932
Hospital and Year Fixed Effects	Yes
Time-Interacted Hospital Controls	Yes
Time-Interacted County Controls	Yes
Basic EMR Control	Yes
Transfer-Adjusted Case Mix Index **(Additional Control)**	Yes
PSA eReporting Interface **(Additional Control)**	Yes
Variance-Covariance Estimator	cluster
Observations	852

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. These models control for two additional hospital attributes—transfer-adjusted case mix index and the hospital's adoption of PSA's electronic reporting interface. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 23 EMR Adoption and Skin Integrity Events (Placebo Outcome, With Additional Controls)

	SE1 b/p	SE2 b/p
Advanced EMR	0.038	0.013
	0.655	0.885
Log Patient Days	-0.060	-0.011
	0.914	0.984
Hospital and Year Fixed Effects	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes
Time-Interacted County Controls	Yes	Yes
Basic EMR Control	Yes	Yes
Transfer-Adjusted Case Mix Index **(Additional Control)**	Yes	Yes
PSA eReporting Interface **(Additional Control)**	Yes	Yes
Variance-Covariance Estimator	cluster	cluster
Observations	808	852

The unit of analysis is hospital-year. The dependent variable is natural log of the count of skin integrity patient safety events. These models control for two additional hospital attributes—transfer-adjusted case mix index and the hospital's adoption of PSA's electronic reporting interface. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A. Not for Publication

Table 24 Advanced EMR, CPOE, and Physician Documentation Adoption and All Events

	A1 b/p	A2 b/p	A3 b/p
CPOE	-0.186		
	0.124		
Physician Documentation		-0.200**	
		0.044	
Advanced EMR			-0.238***
			0.006
Log Patient Days	0.176	0.196	0.174
	0.383	0.342	0.388
Hospital and Year Fixed Effects	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes
Variance-Covariance Estimator	cluster	cluster	cluster
Observations	1135	1135	1135

The unit of analysis is hospital-year. The dependent variable is natural log of the count of all patient safety events. This first analysis has more observations as the models are estimated with HIMSS' reported year of adoption without lags (this is the approach taken by some other researchers such as FLP). *b/p* abbreviate estimated coefficient, and p-value respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 25 CPOE and All Events, Near Misses, Adverse Events, Reached Patients

	Adverse b/p	Near b/p	Reached b/p
CPOE	-0.139*	0.041	-0.031
	0.074	0.803	0.790
Log Patient Days	0.339	0.088	0.096
	0.273	0.743	0.646
Hospital and Year Fixed Effects	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes
Basic EMR Control	No	No	No
Variance-Covariance Estimator	cluster	cluster	cluster
Observations	940	909	946

The unit of analysis is hospital-year. The dependent variable is the natural log of the count of adverse events; near misses; and reached patients, no harm. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 26 Physician Documentation and All Events, Near Misses, Adverse Events, Reached Patients

	Adverse b/p	Near b/p	Reached b/p
Physician Documentation	0.044	-0.293**	-0.291***
	0.593	0.039	0.010
Log Patient Days	0.335	0.134	0.142
	0.269	0.633	0.504
Hospital and Year Fixed Effects	Yes	Yes	Yes
Time-Interacted Hospital Controls	Yes	Yes	Yes
Time-Interacted County Controls	Yes	Yes	Yes
Basic EMR Control	No	No	No
Variance-Covariance Estimator	cluster	cluster	cluster
Observations	940	909	946

The unit of analysis is hospital-year. The dependent variable is the natural log of the count of adverse events; near misses; and reached patients, no harm. *b/p* abbreviates estimated coefficient and p-value, respectively. Standard errors are suppressed from output to conserve space; p-values are included for inference. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Hospital Competition and Data Breaches

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Data breaches affect hundreds of thousands of individuals and firms in the United States every year, and cost hundreds of millions of dollars. Yet, little is known about the impact of industry competition on data breaches because of the difficulty in measuring both industry competition and data breaches. US hospitals provide a nice setting for measurement as hospital markets are geographically defined and most US states require hospitals to report data breaches. We measure hospital competition using the Herfindahl-Hirschman Index (HHI) at the Core Based Statistical Area (CBSA) level and estimate the association between reported data breaches over 2006–2011 and competition by exploiting cross-sectional variation. Surprisingly, we find that increased competition is associated with a decline in the number of reported data breaches. Our main result, if causal, suggests that a 100 point increase in HHI leads to a 5 percent decline in the average count of reported data breach incidents. This main result holds against a number of robustness checks.

Key words: healthcare IT, patient data privacy, data breaches, healthcare competition, information security, IT investments

1. Introduction

Data breaches affect hundreds of thousands of individuals and firms in the United States every year, and cost hundreds of millions of dollars (Ponemon Institute LLC 2014). A recent data breach cost the retailer *Target* more than 100 million US dollars (Sharf 2014). The digital economy depends on the storage and transmission of information that includes personally identifiable information (PII). Data breaches occur when PII is disclosed, either inadvertently or through a malicious act. Despite the importance of the concept, PII is difficult to define (Narayanan and Shmatikov 2010). We define PII as information about individuals that is generally considered private and has the potential of misuse if disclosed.[1]

A question of interest is how competition between firms in an industry affects data breaches, as little is known about this issue despite its importance. In general, this question is hard to answer as defining markets and constructing measures for competition is difficult. However, the hospital industry provides a nice setting as it is relatively easier to define markets as demand and supply for healthcare services are limited by geography. Moreover, hospitals' protection of PII is a particularly salient issue as the need for privacy of health information is a widely accepted notion in the United States. For instance, the Privacy Rule of the Health Insurance Portability and Accountability Act (HIPAA), a federal legislation, explicitly protects health information such as medical records, billing information, and other medical information about individuals. Moreover, legislation in 46 US states (as of August 2011) requires hospitals to report data breaches to the individuals affected by such breaches. The consequences of data breaches can be stark—besides negative publicity and loss of consumer confidence, there may be stiff financial penalties associated with the breach of patient data records. For instance, Stanford Hospital found itself subjected to negative publicity and a $20 million lawsuit due to breach of confidential patient data, when a contractor's actions led to the online exposure from September 2010 to August 2011 of 20,000 Stanford Hospital patient records

[1] The Office of Management and Budget (OMB) defines PII as information about individuals "including, but not limited to, education, financial transactions, medical history, and criminal or employment history and information which can be used to distinguish or trace an individual's identity, such as their name, social security number, date and place of birth, mother's maiden name, biometric records, etc., including any other personal information which is linked or linkable to an individual" (OMB 2006).

(Sack 2011). In June 2010, five California hospitals were fined $675,000 for breach of confidential patient data. These fines were levied despite the fact that some of the hospitals discovered these breaches themselves during audit and disclosed the breaches (Calvan 2010).

Despite these after-the-fact negative consequences, data breaches continue to occur in the US (and elsewhere). Conceptually, incidents of data breaches can be viewed as evidence of lower quality of data protection practices at the firm. So, more broadly, we are addressing the question of the relationship between industry competition and the quality of data protection practices at the firm. We are not aware of any empirical work that examines the role of industry competition on the quality of data protection practices. As noted earlier, two important reasons for lack of significant empirical work on this issue are: (i) Measuring competition is difficult for most industries, as firms operate in national markets (if not international markets) and offer a broad range of products, thus complicating market definition. (ii) Measuring the quality of data protection is difficult as firms do not report their choices for the quality of data protection. Even if we use data breaches as a proxy of firms' quality choices, measurement is problematic as firms are not uniformly required to report incidents of data breaches.

We overcome both these problems by choosing the US hospital markets. First, as hospital markets have relatively crisp geographical boundaries, they facilitate the creation of measures of competition and relevant controls. In addition, a large literature exists that examines the relationship between hospital competition and other outcomes. This literature can inform our definition and measurement of hospital competition. Second, data breaches are more reliably measured in hospital markets as legislation in most US states require hospitals to report data breach incidents.

Economic theory is somewhat ambiguous on the effect of competition on the likelihood or severity of data breaches in hospital markets. As stated earlier, data breaches may be conceptualized as a proxy for the hospitals' quality of data protection. Hospitals will trade-off the cost of increasing quality of data protection against its impact on demand. On one hand, demand for a hospital may be negatively affected if a large scale data breach were to occur in a community with many comparable choices of hospitals. So, hospitals in competitive markets may over-invest in improving

the quality of data protection to guard against a potential loss in demand due to a data breach. On the other hand, hospitals may consider data breach to be a low-risk event and (unless a data breach takes place) their quality of data protection to be largely hidden from consumers. For instance, a hospital's investment in network intrusion detection hardware and software will not be visible to its patients. So, given a budget constraint, hospitals may under-invest in improving the quality of data protection, by over-investing in expensive medical technology and amenities (the so called "medical arms race") as these are more visible to the patients. In summary, economic theory does not provide a definitive answer on how competition will affect the quality of data protection in hospital markets and thus this issue needs to be addressed empirically.

We use approximately 200 reported data breaches in US hospitals over 2006–2011 as a measure of quality of patient data protection practices. We use Core Based Statistical Area (CBSA) both to define hospital markets and as the primary unit of our analysis. We use the number of data breach incident reports as a measure of quality of data protection and Herfindahl-Hirschman Index (HHI) as a measure of competition within each CBSA. We also control for market size, population, population over 65 years, per capita income, and state-level variation in data breach disclosure laws within each CBSA. We also carry out secondary analysis at the hospital level as we can control for hospital size, number of hospital employees, and other hospital-level attributes. We find that increased competition is associated with a decline in the quality of patient data protection. Our main result, if causal, suggests that a 100 point increase in HHI leads to a 5 percent decline in the average count of data breach incidents. This main result holds against a number of robustness checks.

2. Related Literature

Economists, antitrush scholars, courts, and even the general public intuitively think that competition is a good thing. Antitrust law is based on the presumption that competition is good. However, economic theory is not so clear when there are differentiated products. There are two cases to consider viz. when prices are regulated versus when firms set prices. In the case of regulated price

and assuming that prices are more than marginal costs, competition leads to higher quality and consumer welfare, although the impact on social welfare is ambiguous. In the case when firms set prices, the effect of competition is ambiguous even for quality. (Gaynor 2006). Although Medicare regulates a segment of the healthcare market, the overall healthcare market is not regulated. In our study, we do not assume that the regulated and non-regulated segments of hosptial care are separable. Hence, economic theory cannot provide a clearcut answer as to the effect of competition on the quality of patient data security. Yet economic theory can provide us guidance on what factors and their interplay may be important. As Dranove (2011) states, quality choice depends on the following factors: (i) consumer price sensitivity to quality, (ii) price / marginal cost margins, and (iii) marginal cost of increasing quality. So in a physician-patient market, increasing the number of physicians may increase consumer sensitivity to quality but decrease price / marginal cost margins. The overall effect on quality is thus indeterminate. But as we state earlier, these are some of the factors to look for as a guide. In our analysis, Robert Dorfman and Peter O. Steiner (1954) model provides useful insights. Although the model by Robert Dorfman and Peter O. Steiner (1954) is about price and advertising, it can be adapted to study firms' tradeoff between any set of strategic variables. Assuming that the strategic variables are price p and quality z, the Dorfman Steiner condition can be derived as (see Gaynor 2006, p. 7):

$$\frac{z}{p} = \frac{1}{d}\frac{\epsilon_z}{\epsilon_p} \tag{1}$$

Where the firms' marginal costs are $MC = c + dz$, quality elasticity of demand is ϵ_z, and price elasticity of demand is ϵ_p. The point to note here is that an increase in quality elasticity of demand or decrease in price elasticity of demand results in an increase in the ratio of quality to price. If a change in market structure changes the ratio of elasticities, than the ratio of the firms' chosen strategic variables will also change. The model by David Dranove and Mark A. Satterthwaite (1992) also provides similar insights. David Dranove and Mark A. Satterthwaite (1992) study the effect of information on price and quality when the consumer is imperfectly informed about both. They find that better information about prices lead firms to provide sub-optimal levels of quality. As Gaynor

(2006) notes, this is intuitively similar to an increase in the price elasticity of demand, with no increase in the quality elasticity of demand. These are some general guidelines and insights from economic theory that we can bring into our study.

Evidence from econometric studies in the healthcare context is also ambiguous about the impact of competition on various quality measures. As Table 1 shows, some studies find an increase in quality, others find a decrease in quality, and yet others find no effect on quality due to competition. The overall takeaway from Table 1 is that there is no clear pattern that links competition to quality generally and new issues should be examined specifically within their context. Our paper contributes to this literature by examining the effect of competition on the quality of data protection.

In addition, there is growing management literature both on data protection in general and data protection within healthcare in particular. Romanosky, Telang and Acquisti (2011) report that data breach disclosure laws led to a decline in identity theft during the 2002 to 2009 study period. Using analytical and numerical modeling, Romanosky, Sharp and Acquisti (2010) find that data breach disclosure laws may increase firm costs but may lower social costs. Miller and Tucker (2011) paradoxically found that encryption of patient data may actually increase publicized data loss. Our study contributes by examining the effects of market competition on data protection in healthcare markets.

As mentioned earlier, theory does not provide a clear-cut answer on how competition would effect IT security and data protection quality, both in general markets as well as healthcare markets. The extant literature does not address the question of competitive impact on the quality of IT security and data protection practices. We empirically examine this question in the context of healthcare markets.

3. Data Sources and Variable Construction

We collate data from several sources: (i) data breach incidents from Privacy Rights Clearinghouse (PRC), (ii) hospital-level attributes including the market size of the hospital from American Hospi-

tal Association (AHA) annual survey, (iii) hospital-level attributes related to information technologies from the Healthcare Information and Management Systems Society (HIMSS) 2009 Analytics Database, and (iv) county-level attributes from the Department of Health and Human Services Area Health Resource File (AHRF). Table 2 provides summary statistics for select variables in our dataset.

3.1. Data Breach Incidents at Hospitals

For data breach incidents, we source data from the PRC. A grant supported US non-profit corporation, PRC has a stated mission of consumer information and consumer advocacy on issues of personal privacy. PRC data has been used in academic articles as well as popular press such as the Wall Street Journal, New York Times, and numerous other publications (PRC 2013). Starting in the year 2005, PRC has been collecting data breach information for various sectors of the economy including finance, retail, education, and healthcare. PRC updates its data every two days and collates data from multiple sources such as the Open Security Foundation's (OSF's) DataLossDB.org, Databreaches.net, Personal Health Information Privacy (PHIP), and National Association for Information Destruction (in some cases, these secondary sources may be augmenting other data such as PHIP augmenting data from the Department of Health and Human Services medical data breach list). Although some researchers have used OSF as a source (for example, Miller and Tucker 2011), we found PRC to be a more comprehensive source for data breach incident reports.

Our starting dataset includes all incidents reported from January 1, 2006 up to August 22, 2011 for US hospitals as we filter out incidents related to private doctor offices and health insurance companies. We match these hospitals to AHA's unique hospital ID for collating data from other sources. The PRC data not only reports the date and the hospital associated with the data breach incident but also provides additional details on severity and causes of the data breach incident.

Before we describe our variables, it may be worthwhile to briefly discuss as to how data breaches happen and how data breaches get reported.

3.1.1. Data Breach The causes of data breaches can be broadly divided into three categories viz. malicious attacks, unauthorized disclosures, and lost or misplaced protected health information:

(I) *Malicious attacks* take place when individuals access or steal data with malicious intent. These malicious accesses may be through remote hacking into computer systems, physical stealing of computers and storage devices, or insider access of insufficiently protected computer systems. (II) *Unauthorized disclosures* can happen when private patient data is made available to individuals who are not authorized to access this private data. Usually there is no malicious intent. Examples of unauthorized disclosures includes: (a) Wrong person, lab, physician (electronic and physical) (b) Family members (unauthorized) (c) Publicly accessible computer records (d) Insider access due to insufficient access controls (III) *Lost or misplaced protected health information* incidents can happen when laptops or portable storage devices such as thumb drives are lost or misplaced.

Table 3 provides a frequency distribution of the various types of data breach incidents in our data set.

3.1.2. Data Breach Reports We only know about data breach incidents that are reported and there is no way to exactly know how many data breach incidents actually happened—some breaches may never get reported and even some may never get discovered. However, most states have implemented data breach notification laws that mandate hospitals to disclose breaches when personal information is stolen. Given intense media scrutiny, it is highly unlikely that a large data breach can go unreported. In short: (i) Hospitals may be forced to disclose data breaches because the patients reside in a state with mandatory data breach disclosure laws. In some cases, hospitals disclose to avoid breaking the law although the hospital may be dismissive of the impact of the data breach. (ii) Disgruntled (ex-) employees may report a data breaches to settle scores with the hospital. (iii) Consumers, press, or privacy organization may report a data breach discovered by chance (e.g. public posting of private patient information). (iv) Consumers and law enforcement may report data breach discovered as the cause of an indentity theft.

3.1.3. Data Breach Variables We constructed the following variables, which we use as the dependent variable in a number of our models: (I) *Incidents:* The number of data breach incidents that happened at the hospital and CBSA level during the period (2006-2011). The number of

incidents at the CBSA is merely an aggregate of all incidents at the hospitals within that CBSA. This is a count variable. (II) *Incident:* Whether a data breach incident happened at the hospital and CBSA level during the period (2006–2011). This is a binary variable. (III) *Severity:* The severity of the data breach is an ordinal variable coded into three categories as enumerated in Table 4, which also provides a frequency distribution of the levels of severity. Please note that *Severity* is a CBSA-level measure so a frequency of 281 for "No Breach" means that a total of 281 CBSA had no data breaches[2]. (IV) *Number of Records:* The number of records that were breached within a CBSA. This is a count variable. Table 5 provide summary statistics on total records breached and Table 6 provide summary statistics on the number of records breached, given a breach occured. We note that the standard deviation is much larger than the mean number of records breached so it may be helpful to use a logarithm of number of records (given breach) while estimating a model.

3.2. Competition and Market Size

We used American Hospital Association (AHA) yearly survey data set to compute the market size and the Herfindahl-Hirschman Index (HHI) for each CBSA in our study. Hospital market size can be calculated using the total number of hospital beds, in-patient days, or similar measures (e.g. AHA reports adjusted patients days by adjusting in-patient days with the ratio of out-patient revenue and in-patient revenue). Table 7 shows that total beds, in-patient days, and adjusted patient days are significantly and positively correlated (so *HHI* based on either of these measure do not differ much). We thus construct the following variables: (I) *Market Size:* The total number of hospital beds in a CBSA. (II) *HHI:* The sum of squared market shares for hospitals in CBSA, with market shares computed using hospital beds.

It is worthwhile to make a few remarks about the calculation of HHI and its distribution: (i) We counted all hospitals belonging to one hospital system within a market as a single entity. As a hypothetical example, if there are two hospitals in a CBSA owned by the same hospital system, the market is considered a monopoly with an HHI of 10,000. (ii) Since AHA provides yearly data, we first calculated HHI for each CBSA-year and then averaged over the years to obtain

[2] The total CBSA reported here is lower because a few CBSA were dropped due to missing data.

HHI for the CBSA. (iii) As of August 2010, US Federal Trade Commission (FTC) threshold for "highly concentrated" markets is an HHI of over 2500 (Capps and Dranove 2011). Figure 1 shows a histogram of mean HHI, with the HHI=2500 points marked by the red vertical line. Figure 1 suggests that most hospital markets are highly concentrated.

3.3. CBSA Demographics

We used AHRF to compute CBSA-level demographic information such as population, population older than 65, population eligible for medicare, and per capita income. The demographics are reported at the county level in AHRF, which we aggregated to the CBSA level. The variables are: (i) *Population:* The total population residing in a CBSA, calculated as a sum of the population in underlying counties. (ii) *Population Over 65:* Total population over 65 residing in a CBSA (iii) *Per Capita Income:* The weighted average of per capital income at the CBSA level.

3.4. Hospital Data

General attributes of a hospital such as ownership structure and system membership may affect the competitive intensity as well as the quality of data security. We sourced data from AHA yearly survey to construct such general hospital-level variables: (i) *Owner Type:* whether the hospital is government, non-profit, or for-profit, and (ii) *System Member:* whether the hospital is part of a multi-hospital system. Table 9a and 10a provide descriptive statistics on hospital ownership and system membership respectively. We note that most hospitals are not-for-profit and most hospitals belong to a system. Finally, Table 8a provides a tabulation of incidents at the hospitals.

Since a hospital's Information Technology choices will potentially affect data breaches, we further augmented our data with hospital IT variables. We used the Healthcare Information and Management Systems Society 2009 Analytics Database (HIMSS DB) as a data source on hospital information technology. We found that all hospitals included in the HIMSS DB had Electronic Medical Records (EMR) in the year 2009, so we do not include EMR adoption as an independent variable in our analysis. The following hospital-level IT variables were used in our analysis: (i) *FTE:* Full-time equivalent IT employees working at the hospital, (ii) *FTE Security:* Full-time equivalent

employees working in IT security, and (iii) *FTE EMR Help Desk:* Full-time equivalent employees working to support Electronic Medical Records.

3.4.1. Effect on Sample Size of Merging Hospital Data from AHA and HIMSS The AHA survey covers more hospitals than HIMSS, so it is natural that we would lose observations if we attempt to merge the two data sets. We merge AHA and HIMSS data on Medicare number, which results in the loss of hundreds of observations. Finally, there are missing entries in HIMSS data for Information Systems department full-time employee (FTE) counts, which results in further loss of observations in the models that follow. Tables 8b, 9b, and 10b tabulate hospital-level variables after the merge with HIMSS data.

3.5. Other Variables

The reporting of data breaches is potentially influenced by mandatory data breach disclosure laws, where the legislation is at the geographical states level rather than at the federal level. As the state-level legislation was passed at different times, we constructed a control variable, *Law Effective Days*, that counts the days elapsed since the mandatory disclosure legislation was passed.

4. Modeling Framework and Empirical Analysis

As noted earlier, we conceptualize data breach incidents as proxies for hospitals' quality of data protection. Notwithstanding the popular perception that "competition is good", increased competition may lead to decreased quality in certain circumstances. We show using a model (see Appendix B) that under some conditions, in fact, the quality of patient data security will decline. The rationale is as follows: firms are allocating money between improving observable quality (Q) (facilities, clinical care etc) and improving data protection and security (S). Users are more elastic to observable quality attributes. If there is a fixed budget, a monopolist hospital will allocate money to both quality attributes depending on customer elasticity and budget constraint. When firms compete, because users are more elastic to Q, firms will overinvest in Q (i.e this dimension of quality will be higher in competitive markets than monopoly). However, given the budget constraint, competitive firms will under invest in security (S). Given that many hospitals do have fixed budget, they will

shift resources towards more observable quality attributes. It is clear from the literature survey article by Paul M. Lane and Jay D. Lindquist (1988), that patients' hospital choice is driven more by observable factors such as doctors and facilities. Studying the behavior of California hospitals, D. Mukamel, J. Zwanziger and A. Bamezai (2002) found evidence to support the hypothesis that increased price competition may lead hosptials to shift resources from clinical care to facilities, as the latter is more readily observable by the consumer. As users do not observe hospitals' security and privacy practices (except in the aftermath of an adverse event) as much as other dimensions of quality, it is quite likely that competition may not have an expected effect on security and data protection.

The common framework used in empirical work in this area is the structure-conduct-performance (SCP) framework but with a focus on market structure and firm conduct. The usual setup for the SCP framework is as follows: (i) Herfindahl-Hirschman Index (HHI) is used as a measure of competition, (ii) Firm's choice of price or quality-level is used as a measure of firm conduct, and (iii) demand-shifters and cost-shifters are included as controls (see Gaynor 2006, pp. 11, 14-15). The econometric specification usually has the following form:

$$Quality = \beta_0 + \beta_1(Demand\ Shifters) + \beta_2(Cost\ Shifters) + \beta_3(HHI) + \epsilon \tag{2}$$

We employ a similar specification in our study.

4.1. Model Estimators

We are primarily interested in estimating the relationship between the average count of reported data breaches and HHI, identified through the observed heterogeneity at the CBSA-level. This estimated relationship in turn helps us understand the firm's data security quality choice in the face of market competition. Our observed dependent variable is count of data breaches, which naturally suggests a Poisson regression model (PRM) as our basic modeling framework. In general, the data may be over-dispersed, i.e., there may be more variability in the fitted value than is consistent with a Poisson model (Berk and MacDonald 2008). To model potential over-dispersion, we also estimate negative binomial regression models (NBRMs). The NBRM is equivalent to an over-dispersed

PRM in our setting because we assume a zero mean for the over-dispersion parameter ($ln(\delta)$ in Equation 5). For the mean parameter (λ in Equations 3 and 4), the Poisson maximum likelihood estimator (MLE) is fully robust to distributional misspecification. Poisson MLE also maintains some efficiency properties when the distribution is not Poisson (see Wooldridge 2002, chap. 19). Market characteristics such as market size, population, average income of the residents, and others may affect the number of breaches as well as HHI (e.g. one would expect more data breaches in a CBSA with a relatively large population). In our models, we control for these observed market characteristics. To account for heterogeneity at the hospital-level, we repeat our analysis at the hospital-level with more controls, especially IT controls, at the hospital level (as described in a later section).

More formally, we model the number of data breach incident reports ($DBIR$) as a count variable that has a Poisson distribution with mean λ. The natural logarithm of λ is modeled as a linear function of HHI and other variables. Our basic modeling framework can be summarized as:

$$DBIR_i \sim Poisson(\lambda_i) \tag{3}$$

$$ln(\lambda_i) = \beta_0 + \beta_1 HHI_i + \beta_2 (Market\ Size)_i + \beta_3 Population_i + \beta_4 Income_i \tag{4}$$

Where i is an index for the hospital. The over-dispersed case can be modeled by assuming an error δ_i with the following relation with λ_i:

$$ln(\lambda_i) = X\beta + \ln \delta \tag{5}$$

We also assume the mean of $ln(\delta)$ is zero (for identification) and we further assume that δ has a gamma distribution with parameter α_i (see Long 1997, pp. 231-232).

$$\delta_i \sim Gamma(\alpha_i, \alpha_i) \tag{6}$$

δ may be viewed as the combined effect of omitted variables (Gourieroux, Monfort and Trognon 1984) or a source of randomness (Hausman, Hall and Griliches 1984). A likelihood ratio test for the hypothesis $H_0 : \alpha = 0$ provides a test for overdispersion(see Long 1997, p. 237)..

For estimating model parameters, we use maximum likelihood estimators. For estimating standard errors, we use the observed information matrix (OIM) variance-covariance estimator (VCE). The OIM VCE estimates the standard errors and coefficient covariances using the inverse of the negative Hessian matrix (Gould, Pitblado and Sribney 2006, p. 247).

4.2. Main Results

For our primary results, we use variants of models described in Equations (3), (4), (5), and (6) (see page 13). The column labels identify whether we use the PRM or NBRM. The dependent variable in all of these models is the count of data breach incident reports measured at the CBSA-level. Almost all of the explanatory variables in these models (including the focal predictor *HHI*) are measured at the CBSA level, except that the variable *Law Effective Days* is measured at the geographical state level. We did not include geographical state indicators in these models as we include state-level *Law Effective Days* (linearly dependent on geographical state indicators). The direction of HHI is unaffected even if we include state-level indicators and drop *Law Effective Days* as discussed in Subsection 4.3 (on page 15).

The results in Table 11 provide a comparison of estimates on various models. The estimates on *HHI* coefficients are directionally similar and statistically significant in all of these models. We find that an increase in HHI is correlated with a decrease in the average count of data breaches. Table 12 provides detailed results on model NBRM7, which is essentially the same as model NBRM6. The minor difference is that NBRM uses scaled independent variables (HHI, market size, and population) to facilitate discussion. We choose Negative-binomial regression model over Poisson regression model as the likelihood-ratio test of $H_0 : \alpha = 0$ (see Section 4.1) reports a chi-square statistic $\chi^2 = 18.22$ with $P[\chi^2 \geq 18.22|H_0] = 0.000$ providing evidence for overdispersion.[3] Column "factor" in Table 12 provides a multiplicative interpretation of the variable effects. Surprisingly, we find that a 100 points increase in *HHI* leads to a 5 percent decrease in average count of data breaches. A more intuitive example to explain the estimated coefficient is that the change in market

[3] Stata reports *chibar2(01)=18.22* and $Prob >= chibar2 = 0.000$

from five equally-sized firms (with $HHI = 2000$) to four equally-sized firms (with $HHI = 2500$) indicates an approximately 25 percent decrease in the average count of data breaches.

As we noted earlier, one plausible explanation for the observed decline in the quality of data protection is that with increased competition, hospitals allocate more resources to customer observable activities and cut costs on less observable activities such as customer data protection. By focusing resources on relatively more observable activities, the hospitals tradeoff between current revenue vs. the risk of a data breach.

4.3. Robustness

As mentioned earlier, mean estimates from Poisson MLE are robust to distributional assumptions. Table 13 provide further evidence of functional form robustness of our results. In model PRM8 and model NBRM9, we include a quadratic control variable by adding $(Market\ Size)^2$. Model *PRM10* includes indicator variables for US geographical states where the highest percentage of CBSA population resides, but drops *Law Effective Days* (due to linear dependence). We do not show the estimates for the indicator variables in Table 13 to conserve space. Finally, OLS11 estimates a log-linear model using Ordinary Least Squares, with $Log(Incidents)$ as the dependent variable.

Looking at Table 13, we again find that an increase in HHI (i.e. market concentration) is correlated with a decrease in the average count of data breaches. The results are economically and statistically significant in both linear and non-linear models. Table 14 summarizes the evidence from the non-linear models with unscaled independent variables. The first row reports the factor by which average count of data breaches should be multiplied for each unit increase in HHI. The second row reports the p-value for the estimates in the first row. To reiterate, all results in Table 14 are statistically significant and suggest that an increase in HHI is correlated with a decrease in average count of data breaches.

5. Alternate Models at CBSA-level

To further examine the relationship between competition and data protection practices, we estimate models where the dependent variable is different from the models in Section 4.2. Specifically, we

use either *Incident*, or *Severity*, or *Number of Records* (as defined in Subsection 3.1.3 on page 8) as dependent variable in the models that appear in the current section. If our main result holds, we expect to find that these alternative models will also suggest an association between higher competition and lower data security quality.

We first look at the likelihood of the occurrence of a data breach incident in a CBSA. If our main result holds, we would find that increasing HHI (i.e. lower competition) implies a lower likelihood of data breaches (higher data security quality). With CBSA as the unit of analysis, we examine the odds of a data breach incident versus HHI using a logit model. Table 15 summarizes the results of estimated model. The estimates suggest that an increase of 100 point in HHI is associated with a decrease of 2.6 percent in the odds of an incident occuring in the CBSA. We used a robust cluster variance estimator, where the clustering was done on the geographical states. The estimate for HHI are not statistically significant at the 5 percent level, although the p-value is 6 percent. The implication from this model is consistent with our main results i.e. increase in competition is correlated with a decline in the quality of data protection practices.

Next, we look at the relationship between the number of records breached and HHI. While all breaches are unacceptable, some breaches are worse than others due to larger number of records breached. Although number of records breached are counts and a Poisson regression model may seem natural, we can approximate using a normal assumption due to the high average count. Thus, we use a linear specification with log of the number of records breached as the dependent variable. We used Ordinary Least Squares with robust cluster variance estimator, with CBSA as the cluster variable. Table 16 summarizes the model estimates.

The coefficient on HHI is statistically significant and the magnitude suggests that a 100 points increase in HHI may indicate an approximately 25 percent decrease in the number of records breached (ceteris paribus). A clarification about sample size is in order - we deleted[4] 24 observations where the number of records breached was missing in the original data set. Therefore, the sample size is $N = 354$ rather than $N = 380$ as in the earlier models.

[4] We deleted observations with missing data rather than using imputation methods.

Finally we look at the relationship between severity of breach and HHI. The dependent variable for this model is the ordinal variable *Severity* which we define in Subsection 3.1.3 (subsection starts on page 8). We estimate an ordered logistic model to measure the impact of competition (HHI) on severity of breaches. The robust cluster variance estimator uses CBSA for clustering. Table 17 summarizes the estimated model. Please see Subsection **??** for a clarification on sample size. The cut constants divide the latent continuous variable into intervals corresponding to the value of the observed ordinal variable. We will not focus on the latent continuous variable in our interpretation. Instead, we will focus on an interpretation based on odds ratio.[5] Assume $m = 1, 2, 3$ are levels of severity, cut_m is m^{th} cut point, and X is a particular value of HHI (for simplicity of exposition,[6] we ignore the other control variables listed in Table 17). Equation (7) defines[7] $\Omega_m(X)$, the odds of $(Severity > m)$ vs. $(Severity \leq m)$ at $HHI = X$ and Equation (8) defines the log odds ratio, for a unit change in HHI from X to $(X + 1)$.

$$\Omega_m(X) = \frac{Pr(Severity > m|HHI = X)}{Pr(Severity \leq m|HHI = X)} = \exp(cut_m - X\beta_{HHI}) \tag{7}$$

$$\ln \frac{\Omega_m(X+1)}{\Omega_m(X)} = \beta_{HHI} \tag{8}$$

Given the log-linear form of the log odds ratio in Equation (8), the interpretation would be that a 100-point increase in HHI indicates a 3 percent decrease in a $(Severity = 3)$ incident vs. $(Severity < 3)$ incident. Again, we find that an increase in competition is consistent with a decrease in the quality of data protection practices.

6. Alternate Models at Hospital-level

As our final set of models, we investigate the relationship between HHI and the quality of data protection by using hospitals as the unit of our analysis. By analyzing at the hospital-level, we are better able to control for hospital specific heterogeneity.

[5] The odds depend on the cut points for the latent continuous variable as in Equation (7) but we can focus on the estimated coefficients for odds ratios [6] See Long (1997, pp. 138-140) for details. [7] The usual definition of the odds is the reciprocal of our definition here.

6.1. Odds of an Incident and HHI using Simple Logit Regression Model

If more competition is indeed consistent with lower IT security quality, then we would find the odds of a breach to be higher in more competitive markets. To investigate this, we estimate the odds of a breach at a hospital given the HHI for the CBSA (and other control variables) using Logit models. Table 18 summarizes the estimates for a number of logit models. We used a robust cluster variance estimator, where the clustering was done on the CBSA. In addition for the control variables shown in Table 18, we also control for hospital ownership type, hospital system membership, and hospital JCAHO[8] accreditation status.

Except for model L1, the coefficient estimates are not statistically significant and cannot be used for general inference. As descriptive statistic for the given sample, all models suggest a negative relation between HHI and the odds of a breach occuring at a hospital.

6.2. Odds of an Incident and HHI using Multi-level Model

Our data set has an inherent multilevel or hierarchical structure—hospitals are embedded within CBSAs, and CBSAs are embedded within states. Our outcome variable, incident of a data breach during 2006–2011, is measured at the hospital-level. Our focal predictor, HHI, is measured at the CBSA-level, where as control variables are measured at hospital-level, CBSA-level, and geogrpahical state level. Multilevel modeling allows us to take into account the hierarchy in our data.

The non-hierarchical hospital-level model estimates (as in subsection 6.1) suffer from multiple problems. First, the estimate for the coefficient of HHI are not statistically significant when the estimated model includes any control variables - only model L1 in Table 18 has statistically significant coefficient. Second, we cannot include CBSA-level indicators as CBSA-indicators and any of the CBSA-level variables will not be linearly independent. Thus, model estimation requires a strong assumption that the intercept term in these models do not vary at the CBSA-level and the included variables capture all variation attributable to CBSAs. A multi-level model addresses

[8] "An independent, not-for-profit organization, The Joint Commission accredits and certifies more than 19,000 health care organizations and programs in the United States. Joint Commission accreditation and certification is recognized nationwide as a symbol of quality that reflects an organizations commitment to meeting certain performance standards" (Source: http://www.jointcommission.org/about_us/about_the_joint_commission_main.aspx, accessed on Jan 03, 2012).

the later issue, by allowing us to model the CBSA and geographical-state-level heterogeneity as described below. To introduce the model more formally, let us assume that subscripts i, j, k represent the hospital, CBSA, and geographical states in the following equations. We can then write a three-level model as:

$$\Pr(\textit{Incident}_i = 1) = \text{logit}^{-1}[\alpha_{j[i]} + \beta_1 \textit{HHI} + \beta_{\mathbf{2}}(\textit{Hospital-level Preditors})] \tag{9}$$

$$\alpha_j = \gamma_{k[j]} + \beta_{\mathbf{3}}(\textit{CBSA-level Predictors}) + \zeta_j \tag{10}$$

$$\gamma_k = \mu + \eta_k \tag{11}$$

The error terms ζ_j and η_k are assumed to be standard normal random variables. Equation 9 is the main model that estimates the association between *HHI* and the quality of data protection practice. In addition to the focal predictor *HHI*, we also include hospital-level predictors and an intercept term that varies over CBSA. Equation 10 then models the CBSA-level intercept as a normal random variable with mean determined by the CBSA-level predictors and an intercept that varies over geographical states. Thus, we are better able to control for the differences across CBSA and geographical states beyond those captured by the included predictors.

For estimation of these models, we used `lme4`, a multi-level modeling package for the statistical programming language `R`. We only present the estimates on the first-level i.e. hospital-level and suppress the estimates at the CBSA-level and geographical-state level as the latter are not necessary for interpretation. Table 19 provides a summary of estimates for the variables included in the hospital-level model. Since we do not include estimates for the CBSA-level and state-level models, we include the following equations to clarify the functional form at those levels:

$$\alpha_j = \gamma_{k[j]} + \beta_3(\textit{CBSA Size}) + \beta_3(\textit{Average Income}) + \zeta_j \tag{12}$$

$$\gamma_k = \mu + \eta_k \tag{13}$$

The coefficient estimate for *HHI* is statistically significant and implies that a 100-point increase in HHI is consistent with a 1.5 percent decrease in the odds of a data breach incident. The implications from this model are again consistent with our main result.

6.3. Evidence on Higher Observable Quality in Competitive Market

To expain the observed relationship of better data security quality with less competitive markets, we have proffered that hospitals in competitive markets may over-invest in quality signals that are more easily observable to the consumers. Objectively measuring overall hospital quality is not easy and healthcare researchers have usually focused on the outcomes related to very specific ailments such as pneumonia or acute myocardial infarction. Instead of focusing on a the outcome of specific ailments, we instead investigate the relation between HHI and highly visible quality signals such as existence of a residency program, medical school affiliation, and membership in the Council of Teaching Hospitals (COTH). Since the observed outcome variables (medical school affiliation and so on) are binary in nature, it is natural to model the odds of success through a logit specification.

Table 20 summarizes the estimates, where Models Q1, Q2, and Q3 have existence of residency program, medical school affiliation, and COTH membership as outcome variables. We include the usual controls but focus on the sign and statistical significance of the coefficient of HHI in these models. For all of these models, we find that more competitive markets exhibit higher odds of success on these binary variables of highly visible quality signals. While these models do not offer conclusive proof of our resource shifting hypothesis, the relationships suggested by models Q1, Q2, and Q3 along with the theoretical explanation given earlier[9] add to the plausbility of our argument.

7. Conclusion

We find that an increase in competition is associated with a decrease in the number of data breach incident reports. This main result holds against a number of robustness checks, that use alternative: (i) *unit-of-analysis:* CBSA-level analyis or hospital-level analysis, (ii) *outcome measures:* count of incidents, odd of an incident, severity of breach, number of records breached, and (iii) *functional forms:* several different functional forms for different outcome measures. Our main result, if causal, suggests that a 100-point increase in HHI leads to approximately 5 percent decline in the average count of data breach incidents at the CBSA level.

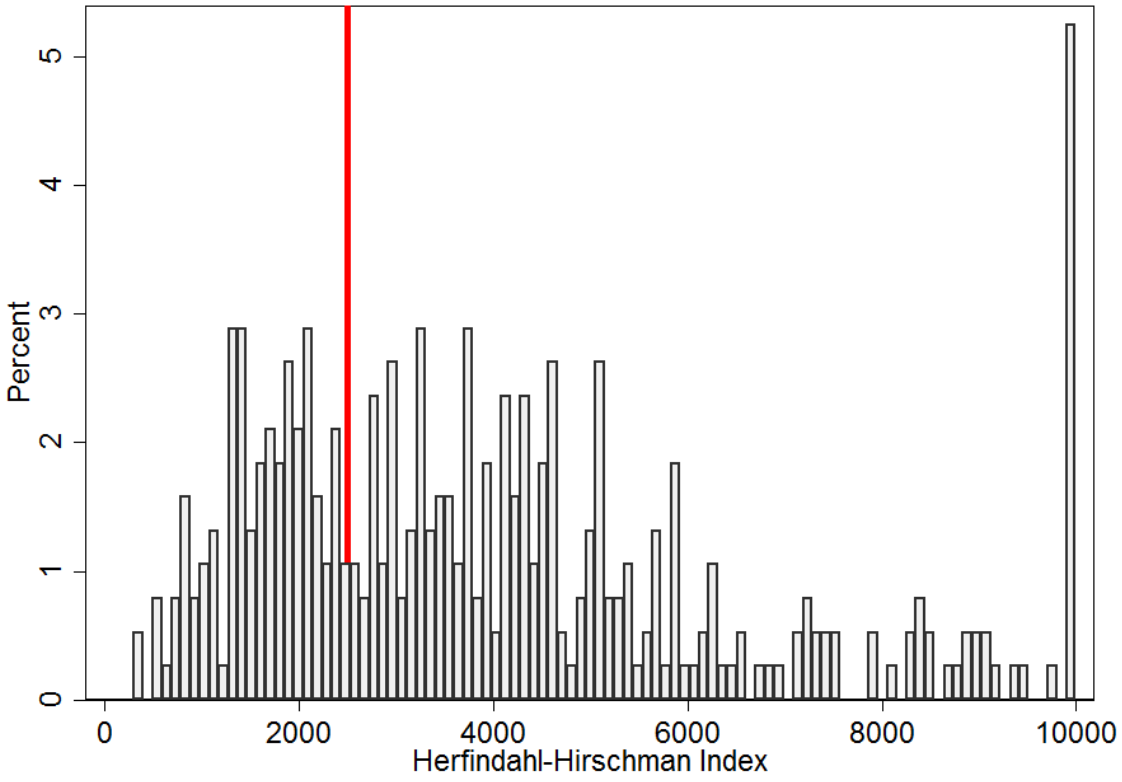
[9] Dorfman-Steiner condition and Dranove-Satterhwaite model.

We conceptualize reported data breaches as proxies for hospitals' quality of data protection. As explanation for our finding, we posit that hospitals in competitive markets may shift resources to more visible quality signals (such as expensive medical technology and amenities) from the less visible quality of data protection. In doing so, the hospitals increase the risk of data breaches. We find support for this explanation both from economic theory (Dorfman-Steiner condition and Dranove, Shanley and Simon (1992)) and from empirical research (Mukamel, Zwanziger and Bamezai 2002). We also find some support for our resource shifting hypothesis from the data as we observe hospital in more competitive markets (ceteris paribus) to have higher likelihood of high quality signals such as residency programs, medical school affiliation, and membership in Council of Teaching Hospitals (COTH).

Our finding may have interesting policy implications. The extant policy has been to let hospitals decide on the level of data security investments and only penalize when a data breach is reported. Although not without its own complications and unintended effects, an alternate policy route would be to require certification to a minimum level of compliance to data protection practice. Our finding may also have indirect implications for general managers and IT managers. While firms in competitive markets may be maximizing profits in expectation, they may be miscalculating the risks of a future breach and thus under-investing the quality of data protection. This may open firms to future losses that have not been correctly anticipated.

8. Figures and Tables

Figure 1 Distribution of HHI



This figure shows the distribution of the Hirschman-Herfindahl Index (HHI) for hospital markets at the CBSA-level (using AHA data from 2006–2011). The red vertical line marks $HHI = 2500$, which is the US Federal Trade Commission threshold for "highly concentrated" markets (Capps and Dranove 2011).

Table 1 Empirical Studies on Competition and Healthcare Quality: Hospitals Set Prices and Quality

(a) Competition Increases Quality

Study	Measures
Joskow (1980)	Excess beds vs. HHI
Robinson and Luft (1985)	Length of stay vs. HHI
Dranove, Shanley and Simon (1992)	High-technology services vs. HHI
Gowrisankaran and Town (2003)	Mortality vs. HHI
Sohn and Rathouz (2003)	Mortality vs. Competition coefficient
Sari (2002)	Quality indicators vs. HHI
Abraham, Gaynor and Vogt (2005)	Quality consumed vs. Number of hospitals

(b) Competition Decreases Quality

Study	Measures
Mukamel, Zwanziger and Bamezai (2002)	Mortality vs. HHI
Volpp et al. (2003)	Mortality vs. Number of competitors
Encinosa et al. (2005)	Patient safety vs. Hospital margin
Propper, Burgess and Green (2004)	Mortality vs. Number of competitors

(c) Competition Has No Effect on Quality

Study	Measures
Ho and Hamilton (2000)	Mortality vs. Merger
Capps (2005)	Patient safety indicators vs. Merger

Table 2 Summary Statistics at CBSA-level

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**
Data Breach Incidents	0.517	(1.385)	0	15
Herfindahl-Hirschman Index	4022.472	(2477.683)	307.371	10000
Market Size (Hospital Beds)	2111.536	(3633.667)	99	44120.333
Population	653217.139	(1154605.876)	55357	11553017.833
Population (eligible for medicare)	92274.541	(144482.482)	4425	1398709
Population (> 65 years)	76341.018	(126618.528)	3103	1302537
Per Capita Income	30495.358	(6057.12)	15748.333	64219.333
Disclosure Law Effective Days	1732.969	(719.009)	0.001	2974
N		381		

Table 3 Frequency Distribution of Type of Data Breach

	Freq.	Percent	Cum.
Hacking or malware	9	4.46	4.46
Insider	46	22.77	27.23
Physical loss	28	13.86	41.09
Portable device	78	38.61	79.70
Stationary device	19	9.41	89.11
Unintended disclosure	20	9.90	99.01
Unknown or other	2	0.99	100.00
Total	202	100.00	

Table 4 Frequency Distribution of Severity of Data Breach in a CBSA

		Freq.	Percent	Cum.
1	No breach	281	79.38	79.38
2	Breach without disclosure of financial data	11	3.11	82.49
3	Breach with disclosure of financial data	62	17.51	100.00
Total		354	100.00	

Table 5 Summary Statistics for Records Breached and Severity

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**
Total Records Breached	28748.741	(205504.05)	0	2204800
Severity	1.38	(0.766)	1	3
N		355		

Table 6 Summary Statistics for Records Breached, Given Breach

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**
Total Records Breached	139805.521	(438061.927)	13	2204800
Log(Records Breached)	8.756	(2.645)	2.565	14.606
N		73		

Table 7 Correlation Between Beds, Inpatient Days, and Adjusted Patient Days (with significance)

Variables	Total Beds	Total Inpatient Days	Adjusted Patient Days
Total Beds	1.000		
Total Inpatient Days	0.974	1.000	
	(0.000)		
Adjusted Patient Days	0.941	0.946	1.000
	(0.000)	(0.000)	

Table 8 Frequency Distribution of Incidents at Hospital-Level

(a) AHA Data Only

		Freq.	Percent	Cum.
0	No Incident	3873	95.87	95.87
1	One or More Incidents	167	4.13	100.00
Total		4040	100.00	

(b) After AHA & HIMSS data merge

		Freq.	Percent	Cum.
0	No Incident	2508	94.29	94.29
1	One or More Incidents	152	5.71	100.00
Total		2660	100.00	

Table 9 Frequency Distribution of Hospital Ownership

(a) AHA Data Only

		Freq.	Percent	Cum.
1	Government, non-federal	597	14.78	14.78
2	Government, federal	162	4.01	18.79
3	Not-for-profit	2029	50.22	69.01
4	For-profit	1252	30.99	100.00
Total		4040	100.00	

(b) After AHA & HIMSS data merge

		Freq.	Percent	Cum.
1	Government, non-federal	349	13.12	13.12
3	Not-for-profit	1705	64.10	77.22
4	For-profit	606	22.78	100.00
Total		2660	100.00	

Table 10 Frequency Distribution of Hospital System Membership

(a) AHA Data Only

		Freq.	Percent	Cum.
0	Not in System	1424	35.25	35.25
1	In a System	2616	64.75	100.00
Total		4040	100.00	

(b) After AHA & HIMSS data merge

		Freq.	Percent	Cum.
0	Not in System	902	33.91	33.91
1	In a System	1758	66.09	100.00
Total		2660	100.00	

Table 11 Data Breach Incident Reports and HHI

	PRM1 b/se/p	PRM2 b/se/p	PRM3 b/se/p	PRM3a b/se/p	PRM3b b/se/p	PRM4 b/se/p	PRM5 b/se/p	NBRM6 b/se/p
incidents								
HHI (by 100)	-0.091***	-0.065***	-0.064***	-0.064***	-0.062***	-0.058***	-0.058***	-0.052***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Market Size		0.000***	0.000	0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		0.000	0.136	0.160	0.311	0.248	0.321	0.686
Population			0.000	0.000	-0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			0.616	0.547	0.789	0.479	0.375	0.296
Population (over 65 years))				-0.000				
				(0.000)				
				0.716				
Population (Medicare eligible)					0.000			
					(0.000)			
					0.507			
Per Capita Income						0.000**	0.000**	0.000*
						(0.000)	(0.000)	(0.000)
						0.023	0.015	0.066
Log(Law Effective Days)							-0.035	-0.034
							(0.022)	(0.026)
							0.113	0.189
Variance-Covariance Estimator	oim	oim	oim	oim	oim	oim	oim	oim
Observations	381	381	381	381	381	381	381	381

The unit of analysis is CBSA. The dependent variable is the count of data breach incident reports, aggregated for the CBSA. *b/se/p* abbreviates estimated coefficient, standard error, and p-value respectively. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12 Data Breach Incident Reports and HHI (Details)

	NBRM7 Coef.	Std. Err.	P-value	Factor
incidents				
HHI (by 100)	-0.052***	(0.009)	0.000	0.94943
Size (by 100)	0.002	(0.006)	0.775	1.00179
Population (by 1000)	0.000	(0.000)	0.453	
Population (over 65 years, by 1000)	0.000	(0.002)	0.913	
Per Capita Income	0.000	(0.000)	0.072	
Log(Law Effective Days)	-0.035	(0.026)	0.188	
Variance-Covariance Estimator	oim			
Observations	381			

The unit of analysis is CBSA. The dependent variable is the count of data breach incident reports, aggregated for the CBSA. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13 Data Breaches Incident Reports and HHI

	PRM8 b/se/p	NBRM9 b/se/p	PRM10 b/se/p	OLS11 b/se/p
main				
HHI (by 100)	-0.046***	-0.039***	-0.050***	-0.015*
	(0.009)	(0.009)	(0.010)	(0.007)
	0.000	0.000	0.000	0.028
Size	0.000**	0.000*	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
	0.003	0.012	0.000	0.007
Size Squared	-0.000**	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
	0.004	0.003	0.000	0.000
Population	-0.000	0.000	-0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
	0.460	0.895	0.037	0.048
Per Capita Income	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	0.020	0.121	0.618	0.613
Log(Law Effective Days)	-0.036	-0.035		-0.037
	(0.023)	(0.026)		(0.039)
	0.112	0.177		0.347
Variance-Covariance Estimator	oim	oim	oim	ols
Observations	381	381	381	381

The unit of analysis is CBSA. The dependent variable is the count of data breach incident reports, aggregated for the CBSA. *b/se/p* abbreviates estimated coefficient, standard error, and p-value respectively. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14 Factor Change in Expected Count of Incidents

	PRM1 factor/p	PRM2 factor/p	PRM3 factor/p	PRM4 factor/p	PRM5 factor/p	NBRM6 factor/p	PRM8 factor/p	NBRM9 factor/p	PRM10 factor/p
incidents									
HHI (by 100)	0.9129	0.9373	0.9384	0.9439	0.9439	0.9494	0.9553	0.9618	0.9508
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 15 Data Breach Incident and HHI

	LOGIT Coef.	Std. Err.	P-value	Factor
incident				
HHI (by 100)	-0.026	(0.014)	0.064	0.97427
Size (by 100)	0.006	(0.017)	0.746	1.00560
Population (by 1000)	0.002**	(0.001)	0.002	
Per Capita Income	-0.024	(0.025)	0.340	
Variance-Covariance Estimator	cluster			
Observations	381			

The unit of analysis is CBSA. The dependent variable is binary, which is set to *true* if an incident occurred at the CBSA-level during 2006–2011 and *false* otherwise. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 16 Number of Records Breached and HHI

	OLS b/se/p
HHI (by 100)	-0.250***
	(0.060)
	0.000
Size (by 100)	-0.111
	(0.246)
	0.651
Population (by 1000)	0.014*
	(0.007)
	0.055
Per Capita Income	0.473
	(0.299)
	0.114
Law Effective Days	0.001
	(0.002)
	0.659
Variance-Covariance Estimator	cluster
Observations	355

The unit of analysis is CBSA. The dependent variable is the natural logarithm of the number of records breached (aggregated for the CBSA). *b/se/p* abbreviates estimated coefficient, standard error, and p-value respectively. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 17 Severity of Breach and HHI

	OLOGIT Coef.	Std. Err.	P-value	Factor
severity				
HHI (by 100)	-0.030*	(0.013)	0.027	0.97078
Size (by 100)	0.016	(0.020)	0.416	1.01615
Population (by 1000)	0.000	(0.000)	0.594	
Per Capita Income	0.032	(0.023)	0.170	
Law Effective Days	0.000	(0.000)	0.559	
cut1				
Constant	2.100*	(0.901)	0.020	
cut2				
Constant	2.365**	(0.901)	0.009	
Variance-Covariance Estimator	cluster			
Observations	355			

The unit of analysis is CBSA. The dependent variable is *Severity*, which is an ordinal variable coded into three categories as enumerated in Table 4. Standard errors are calculated using cluster-robust variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 18 Data Breach Incident and HHI

	L1 b/se/p	L2 b/se/p	L3 b/se/p	L4 b/se/p	L5 b/se/p	L6 b/se/p
incident						
HHI (by 100)	-0.018***	-0.007	-0.013*	-0.012	-0.011	-0.016
	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)	(0.011)
	0.008	0.305	0.096	0.130	0.341	0.138
CBSA Size (by 100)		-0.003	-0.001	-0.004	-0.010	-0.013
		(0.005)	(0.005)	(0.005)	(0.009)	(0.010)
		0.558	0.884	0.333	0.243	0.210
Population (by 1000)		0.000*	0.000**	0.000**	0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		0.084	0.012	0.035	0.795	0.449
Population (>65, by 1000)		-0.001	-0.002	-0.001	0.003	0.005*
		(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
		0.289	0.105	0.642	0.336	0.096
Income (by 1000)		0.023*	0.011	0.005	0.007	-0.028
		(0.012)	(0.013)	(0.012)	(0.018)	(0.032)
		0.068	0.377	0.658	0.675	0.371
System Size (in CBSA)		0.001***	0.000	0.000	0.000	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		0.000	0.405	0.696	0.269	0.011
Hospital Size (by 100)			0.299***	0.243***	0.246***	0.262**
			(0.038)	(0.049)	(0.071)	(0.123)
			0.000	0.000	0.001	0.034
Number of FTE				0.000***	0.000	-0.000
				(0.000)	(0.000)	(0.000)
				0.007	0.571	0.717
FTE in IS					0.003**	0.008**
					(0.001)	(0.004)
					0.019	0.019
FTE in IS Security						0.086
						(0.076)
						0.257
FTE in EMR Support						-0.025**
						(0.010)
						0.013
Intercept	-2.790***	-4.078***	-5.639***	-4.991***	-3.779***	-2.668**
	(0.161)	(0.470)	(0.748)	(0.816)	(0.746)	(1.140)
	0.000	0.000	0.000	0.000	0.000	0.019
Variance-Covariance Estimator	cluster	cluster	cluster	cluster	cluster	cluster
Observations	4040	4040	4040	2646	995	562

The unit of analysis is a hospital. The dependent variable is the binary, which is set to true if a data breach is reported during 2006–2011. *b/se/p* abbreviates estimated coefficient, standard error, and p-value respectively. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 19 Data Breach Incident and HHI

	GLM b/se
HHI (by 100)	-0.015*
	(0.006)
Hospital Size (by 100)	0.309***
	(0.028)
Hospital in System	0.270
	(0.194)
JCAHO Accreditation	1.669**
	(0.604)
Owned by Fed Gov	-0.600
	(0.481)
Not-for-Profit	0.035
	(0.231)
For-profit	-1.632***
	(0.412)
Intercept	-5.320***
	(0.633)
Observations	4033

The model is multi-level, with the main specification at the hospital-level. The dependent variable is binary, which is *true* if a data breach occurred during 2006–2011. HHI is at the CBSA-level but is included in the top-level specification as the same value of HHI applies to all hospitals in a CBSA (which is how we demarcate a market). Hospitals are nested within CBSA, and CBSAs are nested with states. Hence, the intercept at the hospital-level is modeled using CBSA-level predictors and the intercept at the CBSA-level using a state-level fixed effect and a random term. *b/se* abbreviates estimated coefficient and standard error, respectively. Significance levels are: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 20 Observed Hospital Quality and HHI

	Q1 b/se/p	Q2 b/se/p	Q3 b/se/p
main			
HHI (by 100)	-0.020***	-0.015***	-0.029***
	(0.004)	(0.003)	(0.007)
	0.000	0.000	0.000
CBSA Size (by 100)	0.010***	0.009***	0.006
	(0.003)	(0.003)	(0.004)
	0.000	0.000	0.102
Population (by 1000)	-0.000*	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)
	0.054	0.002	0.301
Population (>65, by 1000)	-0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.002)
	0.067	0.362	0.567
Income (by 1000)	0.034***	0.034***	0.034***
	(0.007)	(0.007)	(0.011)
	0.000	0.000	0.002
Hospital Size (by 100)	0.607***	0.584***	0.621***
	(0.026)	(0.026)	(0.031)
	0.000	0.000	0.000
Owner Type	-0.398***	-0.363***	-0.405***
	(0.044)	(0.041)	(0.068)
	0.000	0.000	0.000
Intercept	-1.991***	-1.762***	-3.680***
	(0.318)	(0.295)	(0.498)
	0.000	0.000	0.000
Variance-Covariance Estimator	oim	oim	oim
Observations	4040	4040	4040

The unit of analysis is a hospital. Models Q1, Q2, and Q3 have binary outcomes that are set to *true* if the hospital has a residency program, medical school affiliation, and COTH membership, respectively. *b/se/p* abbreviates estimated coefficient, standard error, and p-value respectively. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix

A. Relation between HHI and Incident Count without Hacks or Malware

Table 21 is included for comparison with Table 12. As is clear, the direction of the result is unchanged and the magnitude changes only very slightly.

Table 21 Data Breach Incidents (without Hacks or Malware) and HHI

	NBRM7			
	b	se	p	factor
HHI (by 100)	-5.12e-02***	(9.30e-03)	0.00	0.95012
Size (by 100)	1.51e-03	(6.41e-03)	0.81	1.00151
Population (by 1000)	1.58e-04	(2.27e-04)	0.49	
Population (over 65 years, by 1000))	5.68e-04	(2.43e-03)	0.82	
Per Capita Income	2.76e-05	(1.55e-05)	0.07	
Log(Law Effective Days)	-4.05e-02	(2.63e-02)	0.12	
Variance-Covariance Estimator	oim			
Observations	381			

The unit of analysis is CBSA. The dependent variable is the count of data breach incident reports (excluding hacks or malware), aggregated for the CBSA. Standard errors are calculated using observed information matrix (oim) variance-covariance estimator. Significance levels are: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B. Theoretical Model of Quality Choice

To recap, we want to understand how firms' optimal choice of two quality attributes - a conspicuous quality attribute and an inconspicuous quality attribute - differ due to market structure. In explaining our empirical results, we have claimed that competitive hospitals may be shifting resources away from inconspicuous data security practice to other more conspicuous activities. In this section, we construct a simple theoretical model that demonstrates that a competitive firm may chose a lower-quality level for an inconspicuous quality attribute (versus a monopoly firm) under plausible conditions. This provides support to our claim that hospitals in competitive markets may be prone to choosing a lower quality level for data security than monopoly hospitals.

B.1. Monopolist

We start with a simple model for a monopolist - the demand is assumed to be linear in conspicuous quality q, inconspicuous quality z, and price p. The monopolist chooses quality levels under a budget constraint B in the first stage and then chooses the optimal price in the second stage. The demand function (with intercept term normalized to 1) and the marginal cost function are assumed to be:

$$d = (1 + aq + bz - cp) \tag{14}$$

$$m = kq + nz; \tag{15}$$

The profit function is concave in p and the first-order conditions lead us to the following equations for profit-maximizing price and the optimal profit:

$$p = \frac{aq + bz + ckq + cnz + 1}{2c} \tag{16}$$

$$\pi = \frac{(aq + bz - c(kq + nz) + 1)^2}{4c} \tag{17}$$

We find optimal q and z by solving the Lagrangian for the optimal profit function:

$$\mathcal{L} = \frac{(aq + bz - c(kq + nz) + 1)^2}{4c} - \lambda(kq + nz - B) \tag{18}$$

Solving the first-order conditions for the Lagrangian simultaneously, we find that the monopolists' profit is maximized at $q = -\frac{-bB+Bcn-n}{bk-an}$, $z = -\frac{-aB+Bck-k}{an-bk}$, and $\lambda = 0$. We use these optimal quality choices of the monopolist as the starting point in investigating the behavior of duopolists.

B.2. Duopolist

Next, we look at a duopoly market where two identical firms, A and B, compete in the market in two stages. In the first stage, firms A and B simultaneously choose their quality levels. In the second stage, firms A and B simultaneously choose their prices. We want to show that under plausible values of the parameters, we obtain a symmetric equilibrium where the profit-maximizing duopolist will increase q and decrease z from the quality choice of the monopolist. The demand functions for the two firms are assumed to be:

$$d_A{=}1{+}\text{a}\ (q_A\ \text{-}\ q_B)\ +\ \text{b}\ (z_A\ \text{-}\ z_B)\ \text{-}\ \text{c}\ (p_A\ \text{-}\ p_B) \tag{19}$$

$$d_B{=}1{+}\text{a}\ (q_B\ \text{-}\ q_A)\ +\ \text{b}\ (z_B\ \text{-}\ z_A)\ \text{-}\ \text{c}\ (p_B\ \text{-}\ p_A) \tag{20}$$

We first solve for Nash Equilibrium for the second stage subgame. The optimal prices are found to be $p_A = \frac{q_A(a+2ck)+q_B(ck-a)+z_A(b+2cn)+z_B(cn-b)+3}{3c}$ and $p_B = \frac{q_A(ck-a)+q_B(a+2ck)+z_A(cn-b)+z_B(b+2cn)+3}{3c}$. The corresponding profit functions at optimal prices are give by $\Pi_A = \frac{(3+(a-ck)q_A+(-a+ck)q_B+(b-cn)(z_A-z_B))^2}{9c}$ and $\Pi_B = \frac{(3+(-a+ck)q_A+(a-ck)q_B-(b-cn)(z_A-z_B))^2}{9c}$.

Since the two firms are identical, we now focus our analysis on Firm A only. The Lagrangian for firm A's objective function in the first stage of the game is given by:

$$\mathcal{L}_A = \frac{(3+(a-ck)q_A+(-a+ck)q_B+(b-cn)(z_A-z_B))^2}{9c}+(\text{B-k}\ q_A\text{-n}\ z_A)\ \lambda_A \tag{21}$$

To make our case, we look for a setup where the duopolist can increase its profits by increasing q and decreasing z. That is, we look for reasonable values for the coefficients in the demand and cost functions that satisfy $\frac{\partial \mathcal{L}_A}{\partial q_A}{>}0$, $\frac{\partial \mathcal{L}_A}{\partial z_A} < 0$, $\frac{\partial^2 \mathcal{L}_A}{\partial z_A \partial q_A} < 0$ if both the firms start at the monopolists' optimal value for q, and z. The region were these conditions are satisfied is given by a>0, b>0, c>0, and either (0<k<$\frac{a}{c}$ and n>$\frac{b}{c}$) or (k>$\frac{a}{c}$ and 0<n<$\frac{b}{c}$). One such set of values is $a = 3, b = \frac{1}{2}, c = 1, n = 2, k = 2, B = 1$. Thus, under the assumptions we have made, a profit-maximizing duopolist will increase q and decrease z relative to the choices of a monopolist. Although the example is constructed with very strong assumptions, it does provide some support to our claim that it is theoretically possible for a competitive firm to choose a lower level of inconspicuous quality than a monopolist.

An online supplement will be posted that provides the detailed steps for this appendix.

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Health Information Technology and Patient Safety: Review and Assessment

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This paper reviews the literature on (i) the factors that affect the adoption of electronic medical records (EMRs) at US hospitals, and (ii) the impact of EMRs on patient safety in US hospitals. The adoption of EMR in US hospitals is positively correlated with hospitals' size, system affiliation, urban location, non-profit ownership structure, and teaching status. There is weak or no evidence that competition, payer mix, and households' or patients' income correlate with hospitals' adoption of EMRs. The literature on the impact of EMR on patient safety is unable to convincingly establish an effect. The studies either use questionable outcome measures such as Patient Safety Indicators for large samples or narrow outcomes such as medication errors for very small samples. In addition to outcome measure issues and sample issues, many of the studies use contestable methods. Given the importance, to managers and public policy makers, of measuring the impact of EMR on patient safety, further research is needed to rigorously identify the impact of EMR on patient safety.

Key words: health IT, patient safety

Acronyms

ADE Adverse Drug Event. 38

AHA American Hospital Association. 16, 21

AHA Annual Survey AHA Annual Survey of Hospitals. 13–15, 17, 19, 21, 32

AHA IT Supplement AHA Annual Survey of Hospitals—IT Supplement. 10, 13–15, 18–22, 32

AHRQ Agency for Healthcare Research and Quality. 26, 31

B-EHR Basic EHR. 13–15

C-EHR Comprehensive EHR. 13–15

CAH Critical Access Hospital. 18, 19

CDR Clinical Data Repository. 5, 7, 10, 21

CDSS Clinical Decision Support System. 5, 7, 8, 10, 21

CMS Centers for Medicare & Medicaid Services. 20, 22

CPOE Computerized Provider Order Entry. 5, 7–10, 13–15, 17, 18, 20, 21, 29, 32, 34, 37–39

DDI Drug-Drug Interaction. 35

DSH Disproportionate Share Hospital. 20

ED Emergency Department. 32, 33

EHR Electronic Health Record. 4, 10, 13–15, 17–23, 32, 33, 39, 40

eMAR Electronic Medication Administration Record. 13–15, 17

EMR Electronic Medical Record. 4–7, 9–17, 19, 21, 22, 24, 27–31, 35

GTT Global Trigger Tools. 26, 27

HADB HIMSS Analytics Database. 4

HCUP Healthcare Cost and Utilization Project. 19

HIMSS Health Information Management Systems Society. 4, 5, 7, 13–17, 19, 21

HITECH Health Information Technology for Economic and Clinical Health Act. 10, 18, 22

IOM Institute of Medicine. 4, 30

LOS Length of Stay. 32, 33

MU Meaningful Use. 14, 19, 22

NIS National (Nationwide) Inpatient Sample. 19

NLP Natural Language Processing. 34

ONC Office of the National Coordinator for Health Information Technology. 17

PACS Picture Archiving and Communication System. 4, 13–15, 17

PD Physician Documentation. 5, 7–10, 18, 21

PSA Pennsylvania Patient Safety Authority. 26

PSI Patient Safety Indicators. 26, 31

ROI Return on Investment. 10

1. Health Information Technology (IT)

Health IT is an all-encompassing term for computer and communication technologies used by health care providers. However, the term *health IT* is used more narrowly in the economics of information technology and medical informatics literature, in which the focus is on software technologies that primarily perform information storage, information retrieval, and information processing functions within the health care context. For example, the recent Institute of Medicine (IOM) report, *Health IT and Patient Safety*, defines health IT to include electronic health records, patient engagement tools, and health information exchanges but to exclude firmware for medical devices such as implantable cardioverter defibrillators.[1] The Health Information Management Systems Society (HIMSS) assists researchers and practitioners in scoping the field by listing 103 distinct applications under 21 categories used in US hospitals in its 2012 version of the HIMSS data set.[2] Table 1 lists HIMSS-defined application categories along with the count of applications in each category (the full list of applications is provided in Table 10 in the appendix). The categories and applications listed in Table 1 (& Table 10) span a wide range—from purely business administration software such as Human Resources and Supply Chain Management to purely medical software and systems such as Radiology & Picture Archiving and Communication System (PACS).[3]

1.1. EMR—Functions and Components

Although many of the IT application categories enumerated in Table 1 play a role in the overall improvement of care quality and patient safety, Electronic Medical Record (EMR) play a particularly salient role and thus EMR systems are widely studied by multiple disciplines.[4] However, precisely defining EMRs is difficult because EMRs continue to evolve. Table 2 lists four features, eight key functionalities, and four components that identify EMR systems (IOM, 2012). The four

[1] IOM, 2011, p. 18 [2] HIMSS calls this data set HIMSS Analytics Database (HADB). We will refer to HADB as HIMSS data set. [3] Health IT spans software that is administrative such as budgeting, cost accounting, and accounts payable to software that support medical functions such as Electronic Health Record (EHR). Noted physician Richard I. Cook, M.D., considers health IT such as electronic medical records, etc., to be core medical functions (IOM, 2011, p. 193). [4] EMR may also be called EHR IOM, 2011, p. 27 or Electronic Patient Record (EPR) (Great Britain House of Commons Health Committee, 2009, p. 60) — there are subtle differences in the meaning of these terms (See Garrett et al., 2011). The hospital industry and medical informatics literature has largely embraced EHR as the preferred term. We follow the economics of IT literature and our health IT data source HIMSS, to refer to this suite of software systems as EMR (and ignore any nuances across EMR, EHR, and EPR).

Table 1 HIMSS Categorization of Information Technology Applications Used in US Hospitals

Category	# Applications
Ambulatory	3
Cardiology & PACS	7
Clinical Systems	9
Document/Forms Management	2
Electronic Medical Record	8
Financial Decision Support	7
General Financials	2
Health Information Management (HIM)	7
Home Health	2
Human Resources	5
IS Infrastructure	4
IS Security	4
Laboratory	6
Nursing	7
Pharmacy	1
Radiology & PACS	12
Revenue Cycle Management	8
Supply Chain Management	4
Telemedicine	1
Transcription	1
Utilization Review/Risk Management	3

This table lists IT application categories and count of applications under the given category as defined in HIMSS dataset 2012. While this table provides counts of application only, Table 10 in the online appendix provides a complete list of 103 distinct applications and their associated categories. Table 3 provides a complete listing of applications for our focal category: *Electronic Medical Record*.

core components in Table 2 also appear in the 2012 HIMSS dataset in its "Electronic Medical Records" category, which we list fully in Table 3.

Henceforth, we focus on four applications — Clinical Data Repository (CDR), Clinical Decision Support System (CDSS), Computerized Provider Order Entry (CPOE), and Physician Documentation (PD). Table 4 provides a synopsis of these applications whereas Section 1.1.1 provides more details. CDR and CDSS are baseline EMR applications whereas CPOE and PD are more advanced EMR applications. As we discuss later, these four components are expected to impact patient outcomes and thus are widely studied. We focus on CPOE and PD as these components are still

Table 2 EMR Features, Functionalities, and Components (IOM, 2012)

Features of EMR Systems
1. longitudinal collection of electronic health information for and about persons
2. electronic access to person- and population-level information by authorized users
3. provision of knowledge and decision support systems, and
4. support for efficient processes for health care delivery
Key Functionalities of EMR Systems
1. health information and data,
2. results management,
3. order entry management,
4. decision support,
5. electronic communication and connectivity,
6. patient support,
7. administrative processes, and
8. reporting and population health management.
Core Components of EMR Systems
1. electronic clinical documentation (e.g. physician documentation),
2. electronic prescribing (e.g., computerized provider order entry),
3. results reporting and management (e.g., clinical data repository), and
4. clinical decision support.

This table list the features, functionalities, and core components of EMR identified in *Health IT and Patient Safety* (IOM, 2012, pp. 27,38).

Table 3 Electronic Medical Records Component Applications

Category	Applications
Electronic Medical Record	Business Intelligence - Clinical Clinical Data Repository Clinical Decision Support System (CDSS) Computerized Practitioner Order Entry (CPOE) Order Entry (Includes Order Communications) Patient Portal Physician Documentation Physician Portal

This table lists all application components categorized by HIMSS as *Electronic Medical Record* in HIMSS dataset 2012.

being adopted, while CDR and CDSS were almost fully adopted by the hospitals in 2012 HIMSS survey. The advanced EMR applications require changes in physician workflows and are considered more difficult to adopt but may also have the most clinical impact.[5] The remaining applications in Table 3 have either been supplanted (e.g. Order Entry by CPOE), are too new (e.g. Business Intelligence), or considered less consequential for patient safety.

Table 4 CDR, CDSS, CPOE, PD

Application	Description
Clinical Data Repository	Stores real-time data about individual patients, storing data that includes patient demographics, clinical information, hospitalization history, billing, and more
Clinical Decision Support Systems	Assist providers in care decision by providing reference information as well as suggestions for care. CDSS generate care suggestions by applying pre-defined rules to patient data e.g. suggestions on drug-allergy contraindications for a specific patient
Computerized Provider Order Entry	Enables providers to electronically add, change, store, and retrieve medication orders, laboratory orders, and radiology orders, and consultation with other providers
Physician Documentation	Consolidates progress notes across hospital departments and thus enable communication between care providers e.g. physicians and pharmacists. Physicians electronically record clinically relevant information in *progress notes* after each encounter with patients

This table briefly describes CDR, CDSS, CPOE, and Physician Documentation.

1.1.1. CDR, CDSS, CPOE, and PD

Clinical Data Repository (CDR): Stores data about individual patients. HIMSS (2009) defines CDR as a "A real-time database that consolidates data from a variety of clinical sources to present a unified view of a single patient. It is optimized to allow clinicians to retrieve data for a single patient rather than to identify a population of patients with common characteristics or to facilitate the management of a specific clinical department. Typical data types which are often found within a CDR include: clinical laboratory test results, patient demographics, pharmacy information, radiology reports and images, pathology reports, hospital admission, discharge and transfer dates, ICD-9/ICD-10 codes, discharge summaries, and progress notes".

[5] Jha, DesRoches, Kralovec, et al., 2010, p. 1952; Jha, DesRoches, Campbell, et al., 2009, pp. 1634–1635.

Clinical Decision Support System (CDSS): Help providers in care decision by providing care recommendations and alerts. CDSSs apply rules of varying levels of complexity to patient specific data such as demographics, problem lists, medication lists, and laboratory results combined with generic medical information (e.g. drug interactions) to infer appropriate suggestions for care. For example, CDSS may check for drug-drug interactions or drug-allergy contraindications to alert care providers in real-time with any problems with potential use of a drug by a specific patient. CDSS may also provide evidence-based reference information to care providers (HealthIT.gov, 2013; ONC, 2011; CMS, 2012a).

Computerized Provider Order Entry (CPOE): Enable providers to electronically add, change, store, and retrieve medication orders, laboratory orders, radiology orders, and consultation with other providers. CPOE enable direct electronic ordering by providers as opposed to electronic transcription by another person from a paper order. CPOE systems' user interface may be desktop-computer based or mobile-device based. The provider orders are electronically transmitted to other units involved in care such as pharmacy, radiology, and laboratory (ONC, 2011; CMS, 2012b).

Physician Documentation PD: (Also known broadly as clinical documentation) Enable providers to electronically enter and retrieve patient's clinical information. Although clinical documentation includes patient demographics, nursing assessments, problem lists, medication lists, and advanced directives, the primary goal of PD is to consolidate progress notes electronically written by physicians after each patient encounter. This ability to consolidate records from multiple disciplines (and providers) separated by time and space is one of the stated drivers for adoption of electronic PD (cf. paper charts) (Payne et al., 2010). For every hospitalized patient, *progress notes* provide a chronology of diagnoses, treatment plans, and other clinically relevant events. The *progress notes* include an admission note, timely and frequent follow-up notes during the stay, and a discharge note. The admission note, written by an attending physician, documents the reason for a patient's admission, the patient's medical condition, and

the treatment plan (among other things). The follow-up notes, written by responsible physicians, document any updates to diagnoses, tests, and treatments due to further encounters with the patient. Finally, the discharge note, written by the attending physician, documents the discharge destination, medications, and follow-up treatment for the patient. Thus, *PD* enables the comparison of patient status over time and serves to communicate clinical findings of one physician to other care provider (such as other physicians, pharmacists, radiologists, etc.) who may have authorized access to patient's records.(Green et al., 2010). In addition to facilitating continuity of care, PD is expected to improve quality and safety of care. A panel of experts commissioned by the Ontario Ministry of Health and Long-Term Care in Canada, qualitatively argued that physician documentations may help improve patient safety as complete and timely information may reduce medication errors, procedural complications, and diagnostic and therapeutic errors. (Ontario Ministry of Health and Long-Term Care, 2006a; Ontario Ministry of Health and Long-Term Care, 2006b). Although hospitals have also used PD to increase reimbursements through better coding, increased reimbursements cannot be the sole reason and may not even be the primary reason for the physicians to adopt electronic documentation. Towers (2013) argues that to overcome physicians' resistance to adopt, they should be encouraged to adopt PD through the message that "good clinical documentation will improve communication, increase recognition of comorbid conditions that are responsive to treatment, validate the care that was provided, and show compliance with quality and safety guidelines."

1.1.2. Sequencing in EMR Adoption Operationally, an EMR system may be implemented by a hospital in phases through several distinct (but sometime integrated) components. These components may have some overlap in functionality: e.g. hospitals may have implemented standalone decision support application initially, but to integrate real-time guidance into providers' workflows, hospitals may separately embed decision support into CPOE. Even after the software is live and operational, these EMR components may have varying level of assimilation in the workflow of the adopting hospital (Angst et al., 2010, p. 1229). *Electronic Medical Record Adoption*

Model (HIMSS, 2014), abbreviated EMRAM^{SM}, describes a staged EMR adoption model for US hospitals, in which hospitals first adopt foundational EMR functionality such as CDR and basic error-checking CDSS in the earlier stages and then adopt more advanced EMR functionality such as CPOE and PD in the later stages. Adler-Milstein, Everson, et al. (2014) used EHR adoption data from the 2008 AHA Annual Survey of Hospitals—IT Supplement (AHA IT Supplement) to find strong evidence of a common adoption sequence amongst hospitals; Table 5 presents the inferred common sequence. CPOE and physician notes (analogous to PD) appear toward the bottom of the sequence, suggesting that hospitals adopt these components in advanced stages of EMR adoption.

1.2. EMR Adoption in US Hospitals

Although health care is an information intensive industry, the adoption of information technology into clinical work processes has lagged other industries such as telecommunication and finance. As EMRs are the primary IT that affects clinical work processes, a number of surveys and qualitative studies have attempted to explain the barriers to adoption of EMR in US hospitals (as I summarize later). Firms adopt IT with the expectation of positive return on their IT investments (and hospitals are no exception), so IT managers usually look for Return on Investment (ROI) studies of adoption at other firms to make a business case to general management for investing in particular IT systems. However, rigorous ROI studies of health IT are few and limited, with most available studies qualitatively describing the expected costs and benefits of health IT. Menachemi and Brooks (2006) summarize a number of studies that demonstrate a positive ROI from health IT. However, the authors note that such ROI studies are either limited to a few settings or to one or few individual IT applications. Menachemi and Brooks (2006) further argue that establishing the hospitals' ROI for health IT is difficult. Health IT, unlike other health technologies such as Computed Tomography (CT) scanners, does not produce revenue. Moreover, the cost savings from health IT may accrue to payers as health IT may improve safety and quality but may also reduce the amount that can be billed by the hospital to the payers.[6] Finally, it is difficult to financially

[6] Due to the peculiar nature of the US health care system,(See Gaynor et al., 2014, for an overview of the industrial organization of US health care) hospitals were initially reluctant in adopting EMR as the hospitals would have absorbed the initial and on-going costs of EMR but the benefits would have accrued to the payers through lower prices for health services. The incentive payments offered by Medicare and Medicaid (due to Health Information Technology for Economic and Clinical Health Act (HITECH)) are meant to overcome the barrier to EMR adoption created by the incentive mismatch.

Table 5 Sequencing of EMR Adoption (Adler-Milstein, Everson, et al., 2014)

Rank	Function category	Specific function
1	Clinical documentation	Patient demographics
2	Results	Radiology reports
3	Results	Laboratory reports
4	Results	Radiology images
5	Clinical documentation	Medication lists
6	Decision support	Drug-drug interaction alerts
7	Decision support	Drugallergy alerts
8	Results	Diagnostic test results
9	Clinical documentation	Discharge summaries
10	Results	Consultant reports
11	Clinical documentation	Nursing assessments
12	Barcode	Laboratory specimens barcode
13	Barcode	Patient ID barcode
14	Decision support	Druglaboratory interaction alerts
15	Results	Diagnostic test images
16	Decision support	Advanced directives
17	Clinical documentation	Drug dosing support
18	Clinical documentation	Problem lists
19	Barcode	Tracking pharmaceuticals barcode
20	Decision support	Clinical reminders
21	Barcode	Pharmaceutical administration barcode
22	CPOE	Radiology tests CPOE
23	CPOE	Laboratory tests CPOE
24	CPOE	Nursing orders CPOE
25	CPOE	Medications CPOE
26	Clinical documentation	Physician notes
27	Decision support	Clinical guidelines
28	CPOE	Consultation requests CPOE

This table shows the sequence of adoption of EMR components as inferred from hospitals surveyed in 2008 AHA IT supplement.

Source: Julia Adler-Milstein, Jordan Everson, et al. (May 22, 2014). "Sequencing of EHR adoption among US hospitals and the impact of meaningful use". In: *Journal of the American Medical Informatics Association*, pages. ISSN: , 1527-974X. DOI: 10.1136/amiajnl-2014-002708. URL: http://jamia.bmj.com/content/early/2014/05/22/amiajnl-2014-002708 (visited on 08/26/2014)

quantify the gains in quality and safety. Due to these challenges, Menachemi and Brooks (2006) note that the literature is sparse and lacking.

Another stream of literature has studied the factors that may be associated with adoption of EMR. We are aware of only two studies—Miller and C. Tucker (2009) and Miller and C. E. Tucker (2014)—that make causal claims about their variable of interest (state laws) and EMR adoption (we summarize these two studies later). The rest of the literature largely studies the association of EMR to various factors. Some factors are similar to those influencing the adoption of enterprise IT in other industries (e.g. size of the firm) whereas other factors are peculiar to health care industry (e.g. payer mix). I summarize the literature on potential contributing factors in Table 6 and further describe individual studies in the rest of the section. The studies I include here are differentiated by the choice of contributing factors, hospital sample, data sources, and the period of study.

Table 6: Predictors of EMR Adoption

Predictors	**Association**	**Adoption Measure**	**Adoption Data Source**	**Study**
Hospital size	Increases	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Increases	Lab, pharmacy, radiology	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
	Increases	EMR, CPOE, PACS, eMAR, Nursing Charts	HIMSS, 2008	Abraham et al. (2011)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008	Jha, DesRoches, Campbell, et al. (2009)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2009	Jha, DesRoches, Kralovec, et al. (2010)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008–2011	DesRoches, Worzala, et al. (2012)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2012	DesRoches, Charles, et al. (2013)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2008–2013	Adler-Milstein, DesRoches, et al. (2014)
	Increases	Clinical HIT index	FL hospital survey, 2003	Hikmet et al. (2008)
	Increases	EHR adoption	AHA Annual Survey, 2008	Shin et al. (2012)
System Affiliation	Increases	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Increases	Lab, pharmacy, radiology	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
	Increases	EMR, CPOE, PACS, eMAR, Nursing Charts	HIMSS, 2008	Abraham et al. (2011)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008	Jha, DesRoches, Campbell, et al. (2009)
	Positive, not significant	Clinical HIT index	FL hospital survey, 2003	Hikmet et al. (2008)
Urban Location	Increases	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Positive, not significant	Lab, pharmacy, radiology	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
	Increases	EMR, CPOE, PACS, eMAR, Nursing Charts	HIMSS, 2008	Abraham et al. (2011)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008	Jha, DesRoches, Campbell, et al. (2009)

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Table 6 – *Continued from previous page*

Predictors	Association	Adoption Measure	Adoption Data Source	Study
	Increases	B-EHR, C-EHR	AHA IT Supplement 2009	Jha, DesRoches, Kralovec, et al. (2010)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008–2011	DesRoches, Worzala, et al. (2012)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2012	DesRoches, Charles, et al. (2013)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2008–2013	Adler-Milstein, DesRoches, et al. (2014)
	Positive, not significant	Clinical HIT index	FL hospital survey, 2003	Hikmet et al. (2008)
	Increases	EHR adoption	AHA Annual Survey, 2008	Shin et al. (2012)
Non-profit Ownership	Not significant	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Not significant	Lab, pharmacy, radiology	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
	Increases	EMR, CPOE, PACS, eMAR, Nursing Charts	HIMSS, 2008	Abraham et al. (2011)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008	Jha, DesRoches, Campbell, et al. (2009)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2009	Jha, DesRoches, Kralovec, et al. (2010)
	Increases	MU	AHA IT Supplement 2008–2011	DesRoches, Worzala, et al. (2012)
	Increases	MU	AHA IT Supplement, 2012	DesRoches, Charles, et al. (2013)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2008–2013	Adler-Milstein, DesRoches, et al. (2014)
	Not significant	Clinical HIT index	FL hospital survey, 2003	Hikmet et al. (2008)
	Increases	EHR adoption	AHA Annual Survey, 2008	Shin et al. (2012)
Competition	Not significant	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Not significant	Lab, pharmacy, radiology	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
Payer Mix (Medicare higher)	Not significant	EMR	HIMSS, 2004	Kazley and Ozcan (2007)

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Table 6 – *Continued from previous page*

Predictors	Association	Adoption Measure	Adoption Data Source	Study
	Increases	Pharmacy IS	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
	Weak	EHR adoption	AHA Annual Survey, 2008	Shin et al. (2012)
Teaching Status	Not significant	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Not significant	Lab, pharmacy, radiology	HIMSS, 1990-2000	Jeffrey S. McCullough (2008)
	Increases	EMR, CPOE, PACS, eMAR, Nursing Charts	HIMSS, 2008	Abraham et al. (2011)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008	Jha, DesRoches, Campbell, et al. (2009)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2009	Jha, DesRoches, Kralovec, et al. (2010)
	Increases	B-EHR, C-EHR	AHA IT Supplement 2008–2011	DesRoches, Worzala, et al. (2012)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2012	DesRoches, Charles, et al. (2013)
	Increases	B-EHR, C-EHR	AHA IT Supplement, 2008–2013	Adler-Milstein, DesRoches, et al. (2014)
	Positive, not significant	EHR adoption	AHA Annual Survey, 2008	Shin et al. (2012)
Household or Patient Income	Not significant	EMR	HIMSS, 2004	Kazley and Ozcan (2007)
	Not significant	B-EHR, C-EHR	AHA IT Supplement 2008	Jha, DesRoches, Shields, et al. (2009)
Change in Unemployment Rate	Increases	EMR	HIMSS, 2004	Kazley and Ozcan (2007)

Drawing from organizational behavior literature and qualitative arguments, Hikmet et al. (2008) hypothesized that larger, urban, system-affiliated, for-profit hospitals will have higher adoption of health IT. The authors test their hypothesis using data from a survey of 98 Florida hospitals between May and October 2003. They find that size has a positive and significant association with clinical HIT index. While the associations for urban location and system-affiliation were positive, the estimates were not statistically significant. Finally, contrary to the authors' hypothesis, the association with for-profit status was negative although statistically not significant.

Kazley and Ozcan (2007) use hospital EMR adoption data from the 2004 HIMSS survey as well as organizational and environmental data from American Hospital Association (AHA), CMS, and ARF. Using a logsitic regression model, they find that hospitals' EMR adoption is significantly associated with type of system affiliation, size, change in unemployment rate, and rurality. The effects of competition, average household income at hospital's location, ownership, teaching status, public payer mix, and operating margin were not statistically significant. The non-adopter hospitals include those that are smaller, more rural, non-system affiliated, and in areas of smaller changes in unemployment rates.

Jeffrey S. McCullough (2008) studies the adoption of laboratory, pharmacy, and radiology systems for 1965 hospitals over 1990–2000 using HIMSS data. Although the focus of this review is EMR adoption, we include Jeffrey S. McCullough (2008) as he studies the adoption of closely related systems. The author found that hospital ownership, competition, or strategic behavior were not associated with hospitals' adoption. In addition, the association between teaching status and the IS systems (under study) was not statistically significant in a multivariate hazard model. However, multi-hospital system membership, payer mix, and hospital scale were associated with higher likelihood of hospitals' adoption of IT: (i) multi-hospital membership markedly increased adoption for all three systems, (ii) scale effect was small to begin with and declined significantly over time, such that the scale effect had almost dissipated by 2000, and (iii) the payer mix only affected pharmacy IS, such that hospitals with higher Medicare inpatient days were more likely to adopt pharmacy IS.

Abraham et al. (2011) use data from 2008 HIMSS Analytics Survey and 2007 AHA Annual Survey to study the prevalence of health IT in US hospitals. The health IT systems included in their study are EMR, CPOE, PACS, eMAR, and Nursing Chart. Their findings can be summarized as follows: (i) hospital size has a slightly positive but diminishing effect on health IT adoption (ii) non-profit hospitals are more likely to adopt these systems (iii) hospitals affiliated with multi-hospital systems are more likely to adopt these systems (iv) teaching hospitals are more likely to adopt CPOE but do not differ for adoption of other health IT systems (v) urban hospitals are more likely to adopt these systems.

Jha, DesRoches, Campbell, et al. (2009) surveyed all acute care general medical and surgical member hospitals about their EHR adoption and received responses from 3049 hospitals (63%). Their study was commissioned by Office of the National Coordinator for Health Information Technology (ONC) to provide accurate measurement of EHR adoption over time. The authors developed new measures for EHR adoption by reviewing prior surveys and developing expert consensus for the new measures. The new measures: (i) Comprehensive EHR Systems (ii) Basic EHR System with Clinical Notes, are defined in Table 7. This table also includes statistics for these measures. The survey was sent as an information technology supplement to the AHA Annual Survey in March 2008, with the in-field period of the survey completing in September 2008. Although the reported adoption percentages are very small for comprehensive (1.5%) and basic (7.6%) electronic-records systems, a much higher percentage of hospitals have reported implementation or resource allocation for physician notes (44%) and CPOE (38%).[7] Based on the authors' statistical analysis, hospitals that were larger, had teaching status, were part of multi-hospital system, and were located in urban areas, reported higher adoption. However, the differences in adoption associated with these factors were small. Also, ownership status mattered little with non-profit hospitals reporting slightly higher adoption compared to for-profit hospitals. Finally, the survey also included questions on barriers and drivers for EHR adoption. For non-adopters, the most cited barriers were lack of capital (74%), concern about maintenance costs (44%), physician resistance (36%), unclear ROI

[7] See Jha, DesRoches, Campbell, et al., 2009, p. 1631.

(32%), and scarcity of IT expertise (30%). Hospitals identified financial incentives as the top two drivers for adoption: (i) reimbursement for EHR use ($\sim$ 80%), (ii) payments for adoption ($\sim$ 75%). Other reasons include technical support for implementation and objective third-party evaluation of EHR products.

Jha, DesRoches, Kralovec, et al. (2010) report survey results from 2009 AHA IT Supplement. As the survey was completed in late 2009, it allowed the authors to explore the change in adoption since the enactment of HITECH Act was passed in early 2009. The authors find that the adoption of either basic or comprehensive EHR increased from 8.7% in 2008 to 11.9% in 2009. Although the adoption remained small for these measures, about one-third of the surveyed hospitals had implemented CPOE and PD in at least one clinical unit.[8] The authors also explore the types of hospitals that have newly adopted EHRs. Using multivariate techniques, the authors find that larger, nonprofit, urban hospitals adopted more than Critical Access Hospital (CAH)s,[9] small and medium-size hospitals, and public and rural hospitals.

In a follow-up study using data from the AHA IT Supplement 2008–2011, DesRoches, Worzala, et al. (2012) found that adoption of either basic EHR or comprehensive EHR increased from 15.1% in 2010 to 26.6 % in 2011. Larger teaching hospitals in the Northeast were more likely to have at least a basic system. The adoption gap between large and small hospitals widened from 15% in 2010 to 22.2% in 2011. Similar gaps were observed between urban vs. rural and teaching vs. non-teaching hospitals. The authors propose that financial incentives may have caused the increased rate of adoption. However, they are unable to test this proposal using data and they acknowledge that increased rate of adoption may just be the S-curve observable in diffusion of other innovations.

[8] See Jha, DesRoches, Kralovec, et al., 2010, pp. 1953–1954. [9] Health Resources and Services Administration (2014) defines critical-access hospitals as "a hospital certified under a set of Medicare Conditions of Participation (CoP), which are structured differently than the acute care hospital CoP. Some of the requirements for CAH certification include having no more than 25 inpatient beds; maintaining an annual average length of stay of no more than 96 hours for acute inpatient care; offering 24-hour, 7-day-a-week emergency care; and being located in a rural area, at least 35 miles drive away from any other hospital or CAH (fewer in some circumstances). The limited size and short stay length allowed to CAHs encourage a focus on providing care for common conditions and outpatient care, while referring other conditions to larger hospitals. Certification allows CAHs to receive cost-based reimbursement from Medicare, instead of standard fixed reimbursement rates. This reimbursement has been shown to enhance the financial performance of small rural hospitals that were losing money prior to CAH conversion and thus reduce hospital closures. CAH status is not ideal for every hospital and each hospital should review its own financial situation, the population it serves, and the care it provides to determine if certification would be advantageous".

DesRoches, Charles, et al. (2013) found that 44% of hospitals surveyed in 2012 had implemented at least basic EHR. They also found that small, rural, Southern, nonteaching hospitals had lowest adoption levels. However, these hospitals also had the highest percentage change in adoption within the respective category. The authors posit that the positive and negative financial incentives from the government may be succeeding in fostering adoption.

Adler-Milstein, DesRoches, et al. (2014) used data from AHA IT Supplement (2008–2013) to report that 59% of hospitals now report adoption of at least basic EMR; however, small and rural hospitals still lag behind in adoption. The hospitals are required to achieve Stage 2 MU attestation by the end of 2014 but only 5.8% of the hospitals are able to meet all Stage 2 requirements. This lack of readiness should be worrisome for hospitals, as they would be subject to penalties in 2015 for failure to meet MU requirements.

Gabriel, Furukawa, et al. (2013) and Gabriel, Jones, et al. (2014) explored the adoption and use of EHR within CAH using data from a CAH specific supplement to the HIMSS Analytics survey from November 21, 2012 and April 30, 2013. Overall, 89% of the CAH use EHR with 27% CAH using EHR exclusively whereas 62% using both EHR and paper. CAHs reported EHR implementation costs (50%), availability of grants/loans to support EHR adoption and use (35%), and broadband implementation costs (23%) as barriers to adoption and use. In addition, 27% CAH reported lack of IT personnel as a barrier to adoption and use. For Stage 1 MU attestation, CAHs (61%) lagged non-CAHs in July 2013.

Shin et al. (2012) examine the relation between EHR adoption and payer mix of the hospital—that is, proportion of Medicare, Medicaid, commercial insurance and managed care caseloads. Shin et al. (2012) use data from the Healthcare Cost and Utilization Project (HCUP)'s National (Nationwide) Inpatient Sample (NIS) for 2007, the 2008 AHA Annual Survey database, and the 2007 Medicare Cost Reports. The payer mix data comes from NIS and AHA Annual Survey whereas the EHR adoption data comes from AHA Annual Survey. The authors find weak relation between payer mix and EHR adoption. The authors' analysis validates the general finding that urban hospitals, non-profit hospitals, system-affiliated hospitals, and larger hospitals are more likely to

adopt EHRs; they also find that teaching status and case mix index had positive but not significant association with adoption. The authors' argue that there is no evidence of indirect influence of payer's generosity on EHR adoption, given that Medicare and Medicaid generally pay less than commercial payers.

Jha, DesRoches, Shields, et al. (2009) explore the association between hospital EHR adpotion and the proportion of patients served by the hospital who are poor. The study uses the Medicare Disproportionate Share Hospital (DSH) index as a proxy variable for proportion of patient served by the hospital who are poor . The authors source the DSH index from the 2007 Impact file compiled by Centers for Medicare & Medicaid Services (CMS) and the data for EHR adoption from the 2008 AHA IT Supplement. For basic and comprehensive EHRs, the study finds the differences in adoption between hospitals, with low and high proportions of poor, to be small and not statistically significant. In addition to the aggregate categories, the study also examined the 24 underlying clinical software functions and found low proportion hospitals to have slightly higher adoption estimates, although the estimates were often not significant. The study also explores the association between EHR adoption, proportion of poor patients, and quality. Hospital quality was summarized for four conditions — acute myocardial infarction, congestive heart failure, pneumonia, and surgical complication prevention — using process measures from Hospital Quality Alliance. The authors find that quality gains associated with EHR are higher for hospitals with higher proportion of poor patients. The quality of high DSH index hospitals is lower for non-adopters, but the higher gains from EHR for high DSH index hospitals almost removes the quality differences for EHR adopters.

Baird et al. (2013) explore the association between corporate governance practices and adoption of health information technology within Integrated Delivery Systems (IDS). They look at two constructs: (i) centralization of IT decision rights, measured by observing the number of Chief Information Officers (CIOs) in the IDS, (ii) strategic alignment, measured by observing if the CIO and Chief Medical Informatics Officer (CMIO) reports to the Chief Executive Officer (CEO). They find slightly positive, but not statistically significant, associations of these two constructs with CPOE adoption.

Finally, we summarize the two causal studies—Miller and C. Tucker, 2009; Miller and C. E. Tucker, 2014. In (Miller and C. Tucker, 2009), the authors find that state privacy laws that impede hospital's release of medical information make the hospitals 24% less likely to adopt EMRs. In a different paper, (Miller and C. E. Tucker, 2014), these authors also find that state laws that facilitate the use of electronic records in malpractice law suits make the hospitals one-third less likely to adopt EMRs.

1.3. Consistency of EMR Adoption Measures

Although measures of EMR adoption have been available from large surveys,[10] the internal consistency and agreements of these measurements has been a concern. Kazley, Mark L. Diana, et al. (2011) explore the consistency of EMR adoption measures as reported in two national surveys—HIMSS Analytics survey and AHA Annual Survey. The authors use HIMSS data for 2005–2008 and treat "Live and operational" status of the enterprise EMR application as EMR adoption. From AHA data from 2007–2008, the authors treat "fully implemented" as EHR adoption, excluding partially implemented EHR. The authors' find good internal consistency for both HIMSS and AHA datasets but limited agreement between HIMSS and AHA datasets. The HIMSS dataset reports higher levels of adoption so the HIMSS measures may have higher false positives. The authors also note that AHA dataset may be more dependable because (i) AHA has several years of experience in surveying hospitals, and (ii) EMR items in AHA Annual Survey have been carefully developed and pilot tested. On further examination, these two reasons for better validity of AHA data are wanting as HIMSS also has several years of experience in surveying hospitals; also, the authors did not use the carefully developed and pilot tested AHA IT Supplement, so their assertion does not follow from their analysis. Further, the ambiguous enterprise EMR application was retired by HIMSS in 2008 and it may have been better to create a measure from the other applications such as CDR, CDSS, CPOE, and PD (especially since the authors use full EMR implementation from AHA data). In a different paper, (Mark L Diana et al., 2011), the same authors explore the consistency of CPOE adoption measures using data from HIMSS Analytics survey (2005–2007)[11] and

[10] For HIMSS, large and long running survey. [11] HIMSS Analytics changed the definition of CPOE between the 2004 and 2005 surveys, so the authors did not use earlier data.

Leapfrog group dataset (2003–2007). The authors find adequate year-to-year consistency within each dataset; however, the level of agreement between the two datasets is low although not low enough to be entirely due to chance.

Everson et al. (2014) explore the reliability and validity of the 2012 AHA IT Supplement. The authors find the survey results to be reliable, as measured by consistent responses to similar questions. In addition, they find the battery of items to be a valid predictor of MU, when compared against the 2011 list of hospitals attested by CMS for MU.

1.4. Meaningful Use

With the HITECH Act, the US government committed $27 billion as incentive payments to hospitals and physicians who adopt EHRs. However, HITECH correctly realizes that it is not mere implementation but meaningful use of EHRs that will accrue benefit to the health care system. Office of the National Coordinator for Health Information Technology (ONC) defines "meaningful use" as "using certified EHR technology to: (i) improve quality, safety, efficiency, and reduce health disparities; (ii) engage patients and family; (iii) improve care coordination, and population and public health; and (iv) maintain privacy and security of patient health information" (ONC, 2014b). CMS, which will provide positive and negative incentives to hospitals and providers for EMR adoption, allowed a 3-stage approach to attaining MU over a five year period. These MU stages and their descriptions are summarized in Table 8.

Blumenthal et al. (2010) describes the final regulation for Stage 1 MU that hospitals should complete in either 2011 or 2012. The Stage 1 criteria included mandatory core objectives as well as 10 menu objectives. Hospitals could choose 5 (or more) out of 10 menu objectives and still achieve Stage 1 MU.

Table 7 Definition of EHR Adoption (Jha, DesRoches, Campbell, et al., 2009, p. 1633)

Requirement	Comprehensive EHR System	Basic EHR System with Clinician Notes	Basic EHR System without Clinician Notes
Clinical documentation			
Demographic Characteristics of patients	X	X	X
Physicians' notes	X	X	
Nursing assessments	X	X	
Problem lists	X	X	X
Medication lists	X	X	X
Discharge summaries	X	X	X
Advanced directives	X		
Test and imaging results			
Laboratory reports	X	X	X
Radiologic reports	X	X	X
Radiologic images	X		
Diagnostic-test results	X	X	X
Diagnostic-test images	X		
Consultant reports	X		
Computerized provider-order entry			
Laboratory tests	X		
Radiologic tests	X		
Medications	X	X	X
Consultation reports	X		
Nursing orders	X		
Decision support	X		
Clinical guidelines	X		
Clinical reminders	X		
Drug-allergy alerts	X		
Drug-drug interaction alerts	X		
Drug-laboratory interaction alerts (e.g., digoxin and low level of serum potassium)	X		
Drug-dose support (e.g., renal dose guidance)	X		
Adoption level — % of hospitals (95% CI)	**1.5 (1.1–2.0)**	7.6 (6.8–8.1)	10.9 (9.7–12.0)

A comprehensive electronic-health-records (EHR) system was defined as a system with electronic functionalities in all clinical units. A basic electronic-records system was defined as a system with electronic functionalities in at least one clinical unit.

Source: Ashish K. Jha, Catherine M. DesRoches, Eric G. Campbell, et al. (2009). "Use of electronic health records in u.s. hospitals". In: 360.16, pp. 1628–1638. ISSN: 0028-4793. DOI: 10.1056/NEJMsa0900592. URL: http://www.nejm.org/doi/full/10.1056/NEJMsa0900592 (visited on 08/20/2014).

Table 8 Meaningful Use of EMR (ONC, 2014a)

Stage	One	Two	Three
Overview	Data capture and sharing	Advance Clinical Process	Improve Outcomes
Period	2011–2012	2014	2016
Meaningful Use Criteria Focus	Electronically capturing health information in a standardized format	More rigorous health information exchange (HIE)	Improving quality, safety, and efficiency, leading to improved health outcomes
	Using that information to track key clinical conditions	Increased requirements for e-prescribing and incorporating lab results	Decision support for national high-priority conditions
	Communicating that information for care coordination processes	Electronic transmission of patient care summaries across multiple settings	Patient access to self-management tools
	Initiating the reporting of clinical quality measures and public health information	More patient-controlled data	Access to comprehensive patient data through patient-centered HIE
	Using information to engage patients and their families in their care		Improving population health

Source: ONC (2014a). *How to Attain Meaningful Use*. URL: http://www.healthit.gov/providers-professionals/how-attain-meaningful-use (visited on 08/25/2014)

2. Patient Safety

> *Medicine used to be simple, ineffective and relatively safe. It is now complex, effective and potentially dangerous (Chantler, 1999).*[12]

Great Britain House of Commons Health Committee (2009) defines patient safety as "freedom, as far as possible, from harm, or risk of harm, caused by medical management (as opposed to harm caused by the natural course of the patient's original illness or condition)". Similarly, the Agency for Healthcare Research and Quality (AHRQ, 2013) defines patient safety as "freedom from accidental or preventable injuries produced by medical care. Thus, practices or interventions that improve patient safety are those that reduce the occurrence of preventable adverse events." Until recently, the medical community viewed medical errors and concomitant harm either as unavoidable side effects of modern medicine or the result of medical treatment by incompetent providers. Leape (1994) argued forcefully that many errors are preventable and many are 'evidence of system flaws not character flaws'. The publication of *To Err Is Human* (IOM, 2000) catapulted the patient safety movement into the medical mainstream. The goal of the patient safety movement is to eliminate preventable patient harm through improved systems and to find solutions when harm is traditionally considered non-preventable.[13]

But to improve patient safety, we first need to measure it[14] as lack of reliable and representative data has been a key challenge. The obvious issue is collecting patient safety event information from more than 5000 US hospitals spread across 50 states without violating patient privacy, while overcoming provider resistance to information sharing due to any perceived harm to their reputation. Recognizing the importance of the issue of patient safety, the Federal government passed The Patient Safety and Quality Improvement Act of 2005 with very broad bi-partisan support.[15] The goal of this legislation "is to improve patient safety by encouraging voluntary and confidential reporting of events that adversely affect patients" (AHRQ, 2008).

[12] Also, quoted in *Health IT and Patient Safety* (see IOM, 2012, p. ix) [13] (Wachter, 2012, pp. 3, 450) [14] "If you cannot measure it, you cannot improve it" (attributed to Lord Kelvin) [15] Passed by unanimous consent in the Senate on July 21, 2005, and passed with 428 Ayes, 3 Nays, and 2 Present/Not Voting in the House of Representatives on July 27, 2005 (Wikipedia, 2013)

There are several different methods for identifying patient safety events, each with their own strengths and shortcomings when applied to epidemiological measurement. We briefly describe some of these methods: (I) *Voluntary or Mandatory Reporting Systems:* expect care providers to report patient safety events to a common organization such as the Pennsylvania Patient Safety Authority.[16] With voluntary reporting, the number of reports from each hospital depends heavily on the culture of the hospital and the propensity of each provider to report an incident. Mandatory reporting systems, as required by Pennsylvania legislation, attempt to promote reporting by both encouraging reporting and penalizing non-reporters. For example, hospitals that do not report a serious event that is discovered by other means may be subject to fines. Reporting systems typically promise confidentiality for clinicians, although some mandatory state programs publish reports attributing events to named institutions. Pennsylvania Patient Safety Authority (PSA) maintains the confidentiality of both clinical and organizational healthcare providers. (II) *Patient Safety Indicators (PSI):* are inferred from administrative billing data using an indicator set such as the 25 PSIs in the July 2010 version of Agency for Healthcare Research and Quality (AHRQ)'s PSIs.[17] Although researchers can construct large nationally representative samples using PSIs, AHRQ and other experts have urged caution when using PSIs.[18] Jha and Classen (2011) write that "... poor-quality measures are plentiful. The best known among these are patient-safety indicators, which use billing data ...".[19] (III) *Global Trigger Tools (GTT):* are sets of defined rules applied in retrospective reviews of medical records to identify "trigger" events that may indicate iatrogenic injury. Further investigation of positive triggers may be needed to determine whether an adverse event occurred. For example, the treatment of a hospitalized patient with an opiate antagonist such as naloxone may trigger further investigation. In head-to-head comparisons with staff reports and administrative data, the GTT typically identify more events, though the other methods identify

[16] Some examples of voluntary reporting programs include JCAHO's Sentinel Event Reporting Program, Institute of Safe Medication Practice's National Medication Errors Reporting Program (MERP), and FDA's Adverse Event Reporting Sytem (Leape, 2002; JCAHO, 2013; ISMP, 2013; FDA, 2013). [17] (Wachter, 2012, pp. 452-453) [18] Please see (Thomas Isaac et al., 2008; White et al., 2009; Romano et al., 2009) and (Wachter, 2012, pp. 8, 17). [19] "Although there is a shortage of good patient-safety metrics, poor-quality measures are plentiful. The best known among these are patient-safety indicators, which use billing data to identify potential complications during a hospitalization. They generally have poor sensitivity and specificity, and their utility varies with hospitals billing practices"

some events the GTT miss. GTT are labor intensive, requiring review by trained analysts. GTT may generate too many alerts and may miss adverse events that have not been prospectively defined. Although GTT appear "to be sensitive in detecting adverse events", they are not extensively validated and largely used as a research tool rather than an operational tool for monitoring safety (Jha and Classen, 2011). Despite their advantages (and even if hospitals can overcome privacy concerns to share data), using GTT to construct a large representative hospital-level panel data set of patient safety events would be very expensive. The high expense comes from the need for highly trained staff to review medical records with positive triggers and conclude if a patient safety event occurred.

2.1. Mechanisms of EMR Impact on Patient Safety

Modern medicine is extremely complex. There are more than 14,000 different diagnoses[20], more than 6,000 drugs, and more than 4,000 medical and surgical procedures[21]. An average patient needed 19.5 full-time equivalent (FTE) hosptial employees for the patient's hospital stay in the mid-1990s compared with 2.5 FTE in the 1970s [22]; if this trend has persisted, the number of FTEs per patient required today would be considerably higher.

The sheer number of diagnoses, drugs, and procedures produces cognitive overload that may lead to errors by competent, caring, and conscientious care providers. As Spear et al. (2005) imply, healthcare needs to "overcome the potential for catastrophe brought on by work complexity, knowledge intensiveness, and variety and volatility of circumstance". Traditionally, the medical profession has responded to progress in biomedical science by introducing specialties and sub-specialties (Cassel et al., 2011; Gawande, 2007). Specialization allows expertise in narrow areas of diagnoses, drugs, and procedures, alleviating the mental load on providers. However, specialization likely increases the number of medical providers involved in the care of each patient and thus exacerbates the communication and coordination burden that inevitably comes from a larger team. Health IT will have an essential role in improving patient safety as managing the increasing complexity of hospital

[20] ...there are 12,420 codes in ICD-10 (14,199 with the fourth-character place of occurrence codes ... (WHO, 2013)
[21] (Gawande, 2011) [22] (Gawande, 2011)

care crosses the threshold of human capacity.[23] Bates et al. (2003) assert that "If medicine is to achieve major gains in quality, it must be transformed, and information technology will play a key part, especially with respect to safety".[24, 25]

The main mechanisms by which we may improve patient safety are by using tools that "can improve communication, make knowledge more readily accessible, require key pieces of information (such as the dose of a drug), assist with calculations, perform checks in real time, assist with monitoring, and provide decision support" (Bates et al., 2003). Each item in this list of mechanisms for improving patient safety, require not only well-designed IT systems but also thoughtful workflow process redesign.

At a basic level, EMRs allow hospitals and other providers to replace paper-based medical record keeping with electronic records. For the record keeping function, some care providers may perceive EMR to be worse than paper records on some dimension such as the relevance of presented data or the value of mandatory input fields which forces care providers to cut-and-paste inaccurate text[26]. However, some of these issues will be resolved as EMRs evolve iteratively based on user feedback; e.g. information architecture and presentation can be improved so that EMR can match and eventually exceed the information efficiency of paper-based systems.

But EMR applications also provide advantages for patient safety that cannot be matched by paper-based systems (IOM, 2011, p. 31). An oft cited example is drug-drug interactions and drug-allergy interactions. In complex cases, the number of prescription drugs needed for treatment may be so large that thinking through all the interactions may overwhelm a human provider. However, such a check will be quite easy for a computer if clear rules existed for drug interactions. It will

[23] Alarmed by this increasing complexity and the resulting egregious medical errors, Johns Hopkins specialist Peter Pronovost pioneered and Harvard surgeon Atul Gawande popularized the use of simple checklists to improve safety outcomes (Henig, 2009; Gawande, 2007). Checklists have proven their worth in other high risk applications such as airline safety, so they may be simple and effective solutions to *some* problems pertaining to patient safety. [24] Bates et al. (2003) further state that safe care is unimaginable without health IT systems such as Computerized Decision Support (CDS). As one example in support of their claims of inevitability of health IT, Bates et al. (2003) adduce identification of drug interactions, which is easier for computers to perform but hard for human prescribers when faced with hundreds of drug choices at multiple dosage levels that need to be individualized to each patient. [25] Richard Irvin Cook, physician and health safety specialist, considers health IT to be an integral part of patient care, going so far as to asserting that health IT such as EMR, digital imaging, provider order entry, etc., are "*core* medical functions" (IOM, 2011, p. 193). [26] For example, a hematologist associated with a major teaching hospital system complained that his EMR inundates him with useless information so the signal-to-noise ratio with EMR is lower. Personal communication with Dr. AJ.

be redundant to specify a long list of mechanisms through which EMR benefits various categories of patient safety events so we refer readers to the cited literature in IOM (2011) for contextual examples.

2.1.1. Health IT May Induce Errors Health IT's effect on patient safety is not always beneficial. In practice, health IT induced errors may cause serious harm to patients. These events may occur through errors in prescribing,[27] poor communication of information due to imperfect human-computer interfaces, and loss of data (IOM, 2011, p. 22). Analysis of health IT related incidents by Magrabi et al. (2010) and Magrabi et al. (2012) points to information input problems, information transfer problems, information output problems, technical problems, and human contributing factors as the broad categories of errors. We focus on medication errors to illustrate some of the mechanisms for health IT induced errors. In a study at a major urban hospital for the period 1997–2004, Koppel et al. (2005) found that CPOE increased 22 types of medication error risks. Some mechanisms include "fragmented CPOE displays that prevent a coherent view of patients medications, pharmacy inventory displays mistaken for dosage guidelines, ignored antibiotic renewal notices placed on paper charts rather than in the CPOE system, separation of functions that facilitate double dosing and incompatible orders, and inflexible ordering formats generating wrong orders". In a more recent study, J. I. Westbrook et al. (2012) found an overall improvement in medication errors due to e-prescribing systems with limited decision support but a major portion of the remaining errors to be induced by the introduction of the new system.[28] As a final illustration, we end our discussion of health IT induced errors by providing an actual report of a health IT induced medication error: "*A patient received two extra doses of oral magnesium oxide 400 mg. Order originally placed by physician for [magnesium] oxide 400 mg [twice a day]*

[27] Health Informatics Professor Georgiou says: "There were many examples of what we called unintended consequences of these systems. If you have a pick list - a site clinician, a nurse, a doctor picks from a list on the computer. Sometimes things look very much the same, it might not be very distinct, and they might pick the wrong one"(J. Westbrook et al., 2013). [28] Although the methods of the study are contestable, the authors (J. I. Westbrook et al., 2012) contend that 'without these system-related errors, the overall clinical error rate in the intervention wards would have declined significantly in the postperiod ... our experience suggests that a high proportion is amenable to remediation through minor system redesign, such as listing the most frequently used option first on drop-down menus, or creating prestructured orders to reduce the need for users to construct complex order sentences. Where system changes cannot be made, areas for targeted training can be identified'.

for two days or four doses. Physician did not place stop date into ProTouch as per proper procedure but instead wrote instructions in the free-text box of ProTouch. When the order was verified by the pharmacist, instructions in the text box [were] not acknowledged. When the nursing staff administered the medication, written instructions [were] not acknowledged. Event [was] discovered by pharmacist after the patient had received six doses of medication" (Sparnon et al., 2012).

3. Evidence for the Impact of Health IT on Patient Safety

Despite the importance of this topic and increased attention from public policy makers, businesses, academia, press, and consumers since the publication of IOM (2000), measuring the impact of various interventions (including health IT) on patient safety has been challenging. In a study of a sample of North Carolina hospitals (2002-2007), Landrigan et al. (2010) found little evidence of improvement in patient safety due to safety training and improvement programs. In their discussion of findings, Landrigan et al. (2010, p. 2130) highlight that use of reliable measurement strategies is needed to assess the overall impact of EMR. Black et al. (2011) note the large gap between postulated and demonstrated benefits of eHealth technologies. Garg et al. (2005) and Reckmann et al. (2009) also express concern about the inadequacy of current literature in measuring the impact of health IT on patient safety and outcomes.

The IOM's book length review of the literature on health information technology (IT) and patient safety, *Health IT and Patient Safety*, focused on the published results from January 2005 to November 2010 (IOM, 2012). I will summarize the relevant findings in IOM (2012), but focus on reviewing and assessing studies published after November 2010. In choosing studies for review, I will closely follow the criteria in IOM, 2012, Appendix B. Hence, my primary goal will be to review experimental studies, observational studies, and systematic reviews that measure the impact of EMR on patient safety. A secondary goal will be to summarize articles that describe the design and implementation of health IT that may be related to safety and quality of health care.

The IOM report *Health IT and Patient Safety*, while acknowledging that the US has adopted health IT with the expectation of safer care, reports that 'the evidence in the literature about the

impact of health IT on patient safety, as opposed to quality, is mixed'[29] and even more explicitly '. . . current literature is inconclusive regarding the overall impact of health IT on patient safety'.[30]

Soumerai et al. (2013) question the evidence on the impact of EMR and contend that the health IT studies are marred by limited samples (usually single site), by weak methodology, and by conflict of interest due to financial ties to the health IT industry.[31]

We summarize some of the reasons why the literature has not been able to settle this question. Since large scale data is hard to gather, many of the studies are done at single or few sites at prominent hospitals (IOM, 2011). For example, Aron et al., 2011 use a 3-year panel from *two* large Asian hospitals to find that automation has a beneficial impact on medical errors. The conclusions of these small sample studies may not generalize. Though the medical informatics literature includes systematic reviews of studies performed at few sites, the conclusions of these reviews are not definitive. Some other studies in this area are written by authors affiliated with the health IT industry, raising the specter of conflict of interest. Measuring patient safety is another challenge. For example some studies have used PSI[32] as outcome measures. With PSI as measure, Parente et al. (2009) find a small beneficial effect of EMR on patient safety, Culler et al. (2007) find no effects or harmful effects of health IT, and Menachemi, Saunders, et al. (2007) find beneficial effects of health IT. As outlined earlier, PSI is a measure with significant limitations.

A closely related stream of research literature investigates the effects of health IT on clinical outcomes such as mortality. Miller and C. E. Tucker (2011), using county-level panel data from the years 1995-2006, find that EMRs reduce neonatal mortality by 16 deaths per 100,000 live births. However, their measure is limited to infant mortality. Jeffery S. McCullough et al. (2013)

[29] (IOM, 2011, pp. 1-2) [30] (IOM, 2011, slide 22) [31] In a recent web article, Harvard professor Stephen Soumerai and University of Pennsylvania researcher Ross Koppel are more blunt on the general question of impact of EMR on outcomes: "*So what? What is the outcome?* . . . where is the evidence to back up the governments and industrys promises of lower mortality, improved health and lower health care costs? Single studies tell us little. Sadly, as many as 90% of health IT studies fail the minimal criteria of the respected international literature syntheses conducted by the Cochrane Collaboration. In other words, studies with weak methodology or sweetheart evaluation arrangements just dont count as evidence. Nevertheless, we know that healthcare IT can improve some processes of care, like reducing duplications of tests, prescribing better drugs for the elderly, and decreasing dosage errors, especially in integrated settings, like certain Kaiser systems. But our and others research shows little or no evidence that such changes result in better health . . . Another difficulty with this research literature is the proliferation of undisclosed financial ties to the industry or with HIT operations. Given the vast sums involved, US policy should be based on rigorous syntheses of the entire literature by unbiased researchers" (Soumerai et al., 2013) [32] Inferred using AHRQ algorithms.

use Medicare admissions data for the years 2002-2007 to examine the role of health IT adoption on patient outcomes for four conditions—acute myocardial infarction, congestive heart failure, coronary artherosclerosis, and pneumonia. They find that health IT improves outcomes for the most severe cases but does not reduce mortality for the median patient. However, the sample was limited to Medicare patients in the fee-for-service program, whose average age is 75 years.

DesRoches, Campbell, et al. (2010) explore the link between EHR adoption and hospitals' quality and efficiency. Their data comes from following sources: (i) 2008 AHA IT Supplement—for hospitals' adoption of basic or comprehensive EHR; (ii) 2008 AHA Annual Survey—for hospitals' bed size, census region, profit status, teaching status, urban or rural, multi-hospital system membership, cardiac intensive care unit; (iii) Hospital Quality Alliance Database—for thirty-day risk-standardized mortality rate and process measures for acute myocardial infarction, congestive heart failure, and pneumonia (process measures used to calculate summary scores); (iv) Medicare Provider Analysis and Review File—for risk-adjusted Length of Stay (LOS), thirty-day readmission rates, and inpatient costs; (v) Medicare Inpatient Impact File—for teaching intensity of hospital (intern-resident-to-bed ratio) and Medicare wage index; and (vi) Area Resource File—for county-level variable such as poverty rate. The study found that EHR adoption was associated with reduced surgical complications but did not find any association between EHR adoption and mortality. No consistent and statistically significant association was found between EHR and LOS, readmission rate, or inpatient costs. CPOE and CDS, taken as individual clinical functions, were associated with marginally better process outcomes. Although this study is carefully conducted, the article seems to imply a causal relation[33] without defending how they avoid bias in their cross-sectional analysis.

Ward, Landman, et al. (2014) compared the 8 operational metrics of 23 Emergency Department (ED)s before and after the implementation of ED EHR. The baseline period was the 6-months prior to EHR implementation and the "after" period was the 6-months to 12-months after the implementation of EHR. The operational metrics were 4 measures of LOS: (i) arrival to provider,

[33] For example, see DesRoches, Campbell, et al., 2010, p. 641, Study Result.

(ii) admitted, (iii) discharged, and (iv) overall length of stay and 4 measures of operational characteristics: (i) left before treatment complete, (ii) significant returns, (iii) overall patient satisfaction, and (iv) provider efficiency. The authors did not find any meaningful association between ED EHR and these operational metrics.

Ward, Froehle, et al. (2014) studied the operational changes at a single ED associated with the introduction of EHR in June 2011. The baseline measurements were taken for a 4 week period whereas the post-implementation measurements were taken over 24 weeks. The authors' find that median LOS increased and patient satisfaction decreased transiently but returned to prior levels in later weeks. However, they find a sustained increase in laboratory order, radiology orders, and medication administration.

4. Conclusion

A review of literature indicates that the adoption of EMR in US hospitals is positively correlated with hospitals' size, system affiliation, urban location, non-profit ownership structure, and teaching status. There is weak or no evidence that competition, payer mix, and households' or patients' income correlate with hospitals' adoption of EMRs. The literature on the impact of EMR on patient safety is unable to convincingly establish an effect. The studies either use questionable outcome measures such as Patient Safety Indicators for large samples or narrow outcomes such as medication errors for very small samples. In addition to outcome measure issues and sample issues, many of the studies use contestable methods. Given the importance, to managers and public policy makers, of measuring the impact of EMR on patient safety, further research is needed to rigorously identify the impact of EMR on patient safety.

5. Health IT, Electronic Medical Records, and Patient Safety

Table 9: Health IT and Patient Safety

Study	Question, Data, Methods, Findings	Assessment
Ramin Khorasani (May 2013). "Can health IT tools enable improved documentation of quality, safety measures, and regulatory requirements in radiology reports?" In: 10.5, pp. 381–382. ISSN: 1558-349X. DOI: 10.1016/j.jacr.2013.02.003	(I) Can Health IT improve documentation of quality and safety measures in radiology reports (II) Qualitative study using Physician Quality Reporting System measure and teaching physician's attestation statement as illustrations. (III) PACS with integrated speech recognition and report templates (IV) Speed recognition software and standard report templates may help in improving documentation. Recommends thoughtful trade-off between few generalized templates versus many specialized templates.	Provides qualitative arguments but no hard evidence on how the use of health IT such as speech recognition and report templates impacts patient safety.
Luciano M. Prevedello et al. (Aug. 2013). "Can health IT tools enable improved documentation of quality, safety measures, and regulatory requirements in radiology reports? part 2". In: 10.8, pp. 635–636. ISSN: 1558-349X. DOI: 10.1016/j.jacr.2013.05.007	(I) Can Health IT improve documentation of quality and safety measures in radiology reports (II) Qualitative study using Physician Quality Reporting System measure and teaching physician's attestation statement as illustrations. (III) PACS with NLP, decision support, and integration with CPOE (IV) NLP may be used to check adherence to documentation requirements; alerts may be used to notify recognized defects.	Provides qualitative arguments but no hard evidence on how the use of health IT such NLP, decision support, and integration with CPOE impacts patient safety.

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Table 9 – *Continued from previous page*

Study	Question, Data, Methods, Findings	Assessment
Sarah P. Slight, Diane L. Seger, et al. (2013). "Are we heeding the warning signs? examining providers' overrides of computerized drug-drug interaction alerts in primary care". In: 8.12, e85071. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0085071	(I) Evaluate providers' DDI overrides in a "tuned" setting with relatively few false positive alerts (II) Cross-sectional observation study (III) Jan 1, 2009 to Dec 31, 2011 (IV) 36 primary care practices with 1718 prescribers affiliated with two Harvard teaching hospitals;[34] 24,849 DDI alerts generated with 40% accepted; top 62 providers with highest override rate studied (V) EMR with decision support (VI) 68.2% override appropriate; providers' continue to override DDI alerts even within an optimized system	Indirectly provides evidence that EMR with decision support may reduce DDI if providers' accept alerts. Currently, a high number of alerts are being overriden (60%); from a selected sample of overrides, about 30% of the overrides were inappropriate. Limited external validity.
Pascale Carayon et al. (Sept. 1, 2013). "Macroergonomics in healthcare quality and patient safety". In: 8.1, pp. 4–54. ISSN: 1557-234X. DOI: 10.1177/1557234X13492976	(I) Advocates use of human factors and ergonomics (HFE) for improving health IT's impact on patient safety (II) Qualitative study (III) Suggest health IT should address individual informational needs (providers, patients), workflow needs, and team collaboration needs	Discusses how using HFE in health IT design may improve patient safety but does not provide hard evidence.

Continued on next page

[34] BWH, MGH part of Partners HealthCare

Table 9 – *Continued from previous page*

Study	Question, Data, Methods, Findings	Assessment
Sarah P. Slight and David W. Bates (Apr. 24, 2014). "A risk-based regulatory framework for health IT: recommendations of the FDASIA working group". In: ISSN: 1527-974X. DOI: 10.1136/amiajnl-2014-002638	(I) What health IT need regulation because of FDA Safety and Innovation Act (FDASIA) (II) Electronic health records (among others) (III) Qualitative study (IV) Recommends that: {a} health IT must not be subject to FDA pre-market notification (except in high risk products such as computer aided diagnostics), {b} post-market surveillance mechanism as well as post-implementation testing	Summarizes the report of FDASIA Working Group on health IT regulation. Speculates that health IT (in aggregate) is highly beneficial to safety but desired benefits do not follow in all cases and there are unintended (negative) consequences.
Jeffrey Avansino et al. (2012). "Effects of CPOE on provider cognitive workload: a randomized crossover trial". In: 130.3, e547–e552. URL: http://pediatrics.aappublications.org/content/130/3/e547.short (visited on 08/14/2014)	(I) Effect of systematically developed order sets on usability, cognitive workload, and conformance to established clinical guidelines (CG), compared to ad hoc order sets, for post operative management of perforated and nonperforated appendicitis in children (II) Convenience sample of seven surgeons (3 residents, 3 fellows, 1 attending) in a regional pediatric hospital[35] (III) July and August 2009 (IV) Cross-over trial; non-human subject research (V) Compared to ad hoc order sets, systematically developed order sets have better usability, cognitive workload, and conformance to CG	Small convenience sample at one hospital for a specific condition in a simulated rather than clinical setting; study lacks external validity. Use of systematic order sets may improve patient safety due to conformance to CG but there is no hard evidence provided for patient safety improvements

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[35] Seattle's Childrens Hospital)

Table 9 – *Continued from previous page*

Study	Question, Data, Methods, Findings	Assessment
Julie Chan et al. (2011). "Does user-centred design affect the efficiency, usability and safety of CPOE order sets?" In: 18.3, pp. 276–281. URL: http://jamia.bmj.com/lookup/pmid?view=full&pmid=21486886 (visited on 08/14/2014)	(I) Compare baseline CPOE order sets (CPOE Test), order sets developed using user-centered design principles (CPOE UCD), and paper order sets (Paper) (II) CPOE order sets (really the evaluation is for user-centered design) (III) Completion time (efficiency), request for assistance (usability), errors in submitted orders (safety) (IV) 27 physicians, residents, and medical students in an academic hospital in Toronto, Canada[36]; 108 order sets completed—4 per participant—for four common general internal medicine conditions: community acquired pnemonia (CAP), exacerbation of chronic obstructive pulmonary disease (COPD), acute stroke, and urinary tract infection. (V) User Centered Design format more efficient and usable than CPOE Test; No statistically significant difference in proportion of orders sets with at least one error; CPOE Test has slightly higher proportion of harmful errors than Paper.	Small convenience sample at one hospital for 4 specific conditions in a simulated rather than clinical setting; study lacks external validity. No statistically significant difference between Paper and CPOE UCD for errors.

Continued on next page

[36] Sunnybrook Health Sciences Centre

Table 9 – *Continued from previous page*

Study	Question, Data, Methods, Findings	Assessment
Raman Khanna et al. (2014). "Computerized physician order entry promise, perils, and experience". In: 4.1, pp. 26–33. URL: http://nho.sagepub.com/content/4/1/26.short (visited on 08/14/2014)	(I) Reviews literature on CPOE, CDSS and describes CPOE roll-out (II) Qualitative study (III) CPOE, CDSS, order sets (IV) EvergreenHealth in Seattle, Washington (V) CPOE sped some orders (e.g. statim chest x-rays) but slowed others (e.g. brain MRI); also, physician workflow was altered and made more rigid in some cases. Clinicians generally adopted health IT as they wanted the system back during an outage	Qualitative study that implies that health IT may benefit safety in some areas and potentially harm in some other (e.g. rigid drug administration). No definitive benefits or harm established.
Alexander A. Leung et al. (2012). "Impact of vendor computerized physician order entry in community hospitals". In: 27.7, pp. 801–807. URL: http://link.springer.com/article/10.1007/s11606-012-1987-7 (visited on 08/11/2014)	(I) Evaluates the impact of vendor CPOE systems on the frequency of ADE rates (II) January 2005 to September 2010 (III) 5 community hospitals; 2000 charts reviewed (IV) Primary outcome was preventable ADE rates; secondary outcome was potential ADE and overall ADEs (V) Prospective before-and-after study (VI) Reduction of 34% in preventable ADEs but increase of 29.5% in potential ADEs. Overall ADE rate increased.	This study is more carefully designed as it observes five hospitals before and after CPOE adoption and infers ADEs using trigger tools, implying high quality measurement of both the treatment and outcome. However, the results still appeared to be biased. A differences-and-differences analysis with hospital and year fixed-effects as well as other time-varying controls would be the best way to analyze the data. However, the analysis in the paper seems to be missing the controls for these confounders (the statistical analysis section and results tables are hard to follow).

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Table 9 – *Continued from previous page*

Study	Question, Data, Methods, Findings	Assessment
Elliot J. Wasser et al. (Dec. 2013). "Optimizing radiologist e-prescribing of CT oral contrast agent using a protocoling portal". In: 201.6, pp. 1298–1302. ISSN: 1546-3141. DOI: 10.2214/AJR.12.9982	(I) Quantify radiologists' time expenditure with Computed Tomography (CT) oral contrast media order via CPOE; determine radiologists' perception about patient safety (II) 13 residents and fellows at an urban tertiary academic medical center for ordering; 40 radiologist for perceptions survey (III) March 20, 2012 through April 2, 2012 (IV) 52.5% survey respondents indicate that physician ordering (vs. nurse or technician ordering) improved patient safety; 15% respondents thought that order entry was very or extremely disruptive to workflow	States physician's perception about patient safety rather than actual measurement; in addition, the variable of interest is physician ordering rather than health IT
Dean F. Sittig et al. (2012). "Electronic health records and national patient-safety goals". In: *New England Journal of Medicine* 367.19, pp. 1854–1860. URL: http://www.nejm.org/doi/full/10.1056/NEJMsb1205420 (visited on 11/04/2013)	(I) Proposes national patient-safety goals for electronic health records (II) Qualitative arguments (III) A 3-phase approach is suggested, (i) address safety concerns unique to EHR technology, (ii) mitigate safety concerns arising from failure to use EHR appropriately, (iii) use EHRs to monitor and improve patient safety	This paper proposes a 3-phase approach to setting patient-safety goals for EHRs, providing anecdotes and literature references for why the goals qualitatitvely make sense. The proposed phases would be familiar to anyone working with enterprise IT as these roughly map to getting the enterprise IT implementation right (with appropriate failover plans), getting the workflows right, and finally using the information generated by IT to learn about the processes and drive further improvements.

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Table 9 – *Continued from previous page*

Study	Question, Data, Methods, Findings	Assessment
Hardeep Singh, David C. Classen, et al. (2011). "Creating an oversight infrastructure for electronic health record-related patient safety hazards". In: 7.4, p. 169. URL: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3677059/ (visited on 08/11/2014)	(I) Propose creation of a national EHR oversight program to provide dedicated surveillance of EHR-related safety hazards and to promote learning from identified errors, close calls, and adverse events. Suggests data gathering, investigation and analysis, and regulation at the national level (II) Qualitative study	Qualitative argument in response to the risks posed to patient safety due to adoption of EHRs (e.g. EHR outages). Suggests organizational setup, functions, and powers of the entities to realize their proposal.
Hardeep Singh, Joan S. Ash, et al. (2013). "Safety assurance factors for electronic health record resilience (SAFER): study protocol". In: 13.1, p. 46. URL: http://www.biomedcentral.com/1472-6947/13/46/ (visited on 08/11/2014)	(I) Describes study protocol for for developing self-assessment guides to be used by health care institution to evaluate high-risk components of EHR-enabled clinical work systems (II) Solicit input from subject matter experts and stakeholders to develop guidelines focused on 9 specific risk areas	This study addresses the concern that EHR may introduce new types of patient harm and so these risks should be proactively managed. The authors describe a study protocol so the risk-assessment guides may take a while to develop. It is unclear how well these guides would be adopted upon release.

Appendices

A. Details

Table 10: Health IT Categories and Applications from HIMSS Analytics Database, 2012

Category	**Applications**
Ambulatory	Ambulatory EMR
	Ambulatory PACS
	Practice Management
Cardiology & PACS	Cardiology - CT (Computerized Tomography)
	Cardiology - Cath Lab
	Cardiology - Echocardiology
	Cardiology - Intravascular Ultrasound
	Cardiology - Nuclear Cardiology
	Cardiology 3D Image/Display
	Cardiology Information System
Clinical Systems	Anesthesia Information Management System (AIMS)
	Emergency Department Information System (EDIS)
	Intensive Care
	OR Scheduling
	Obstetrical Systems (Labor and Delivery)
	Oncology Information System
	Operating Room (Surgery) - Post-Operative
	Operating Room (Surgery) - Pre-Operative
	Respiratory Care Information System
Document/Forms Management	Document Management
	Electronic Forms Management
Electronic Medical Record	Business Intelligence - Clinical
	Clinical Data Repository
	Clinical Decision Support System (CDSS)
	Computerized Practitioner Order Entry (CPOE)
	Order Entry (Includes Order Communications)
	Patient Portal
	Physician Documentation
	Physician Portal
Financial Decision Support	Budgeting
	Business Intelligence - Financial
	Contract Management
	Cost Accounting
	Data Warehousing/Mining - Financial
	Executive Information System
	Financial Modeling
General Financials	Accounts Payable
	General Ledger
Health Information Management (HIM)	Abstracting
	Chart Deficiency
	Chart Tracking/Locator
	Computer Assisted Coding
	Dictation
	Dictation with Speech Recognition
	Encoder
Home Health	Home Health Administrative
	Home Health Clinical
Human Resources	Benefits Administration
	Payroll
	Personnel Management
	Staff Scheduling
	Time and Attendance
IS Infrastructure	DBMS
	Disaster Recovery System
	Interface Engines
	Virtualization Software
IS Security	Encryption
	Firewall
	Single Sign-On
	Spam/Spyware Filter
Laboratory	Anatomical Pathology
	Blood Bank

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Table 10 – *Continued from previous page*

Category	**Applications**
	Laboratory - Molecular Diagnostics
	Laboratory - Outreach Services
	Laboratory Information System
	Microbiology
Nursing	Electronic Medication Administration Record (EMAR)
	Infection Surveillance System
	Medication Reconciliation Software
	Nurse Acuity
	Nurse Call System
	Nurse Staffing/Scheduling
	Nursing Documentation
Pharmacy	Pharmacy Management System
Radiology & PACS	Radiology - Angiography
	Radiology - CR (Computed Radiography)
	Radiology - CT (Computerized Tomography)
	Radiology - DF (Digital Fluoroscopy)
	Radiology - DR (Digital Radiography)
	Radiology - Digital Mammography
	Radiology - MRI (Magnetic Resonance Imaging)
	Radiology - Nuclear Medicine
	Radiology - Orthopedic
	Radiology - US (Ultrasound)
	Radiology 3D Image/Display
	Radiology Information System
Revenue Cycle Management	ADT/Registration
	Bed Management
	Credit/Collections
	Electronic Data Interchange (EDI) - Clearing House Vendor
	Enterprise Master Person Index (EMPI)
	Medical Necessity Checking Content
	Patient Billing
	Patient Scheduling
Supply Chain Management	Asset Tracking/Management
	Enterprise Resource Planning
	Materials Management
	Real Time Location Solution (RTLS)
Telemedicine	Telemedicine
Transcription	In-House Transcription
Utilization Review/Risk Management	Case Mix Management
	Data Warehousing/Mining - Clinical
	Outcomes and Quality Management

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