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

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Abstract. The risk of patient harm resulting from medical care affects hundreds of thousands of patients and costs tens of billions of dollars every year. Advanced electronic medical records (EMRs) are expected to improve patient safety, but the evidence of their impact on patient safety is inconclusive. A key challenge to evaluating advanced EMRs' impact has been the lack of reliable patient safety data. We address this issue by analyzing a new patient safety data set from the Pennsylvania Patient Safety Authority (PSA), a state agency that aggregates patient safety data from Pennsylvania hospitals. Using a 2005–2014 panel from PSA, we identify advanced EMRs' effect using the difference-in-differences method. We find that advanced EMRs lead to a 17.5% decline in patient safety events, driven by reductions in medication errors, falls, and complication errors. Further, our analysis shows a decline in medium- and high-severity events.

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Keywords: information systems • healthcare • IT policy and management • economics of IS • patient safety • electronic medical records (EMR) • medication errors

1. Introduction

According to the landmark Institute of Medicine (IOM) report *To Err is Human*: *Building a Safer Health System*, 44,000 to 98,000 people die each year in U.S. hospitals from preventable medical errors (Kohn et al. 2000). 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).

Health information technology (IT) is widely considered to be a 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 found the literature unconvincing because of the use of limited samples (one or few prominent hospitals), weak methodology, and conflict of interest arising from researchers' financial ties to the health IT industry. Furthermore, systematic reviews of the literature do not suggest a general pattern of impact of health IT on patient safety (Black et al. 2011). 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 the impact of advanced electronic medical records (EMRs)[1] on patient safety specifically through the empirical analysis of a data set of Pennsylvania hospitals from 2005 through 2014. In particular, our data set contains new and 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. We combine this patient safety data from PSA with advanced EMR adoption data as well as control variables obtained from several sources. The resulting panel data set allows us to identify the impact of hospitals' adoption of advanced EMRs on patient safety events using the difference-in-differences method. We use a

number of robustness checks to validate our results. Our main finding is that advanced EMRs lead to a 17.5% decline in patient safety events. Our data allows us to explore various subcategories of clinical processes and examine how EMRs affects these categories. We find that the overall decline is driven by reductions in several important subcategories—medication errors decline by 21.6%, falls decline by 17.8%, and complications decline by 16.6%. Our analysis further shows that within these subcategories, the impact of advanced EMRs extends to all severity levels. Advanced EMRs not only reduce medium severity events (by 22.5%), they also have a large effect on high severity events (about a 16.2% decline), suggesting large-scale economic benefits. These findings that advanced EMRs improve patient safety would be interesting to healthcare policy makers and hospital managers.

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

2.1. Health IT and Electronic Medical Records

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 there is no consensus on what exactly constitutes EMRs. For instance, the Healthcare Information and Management Systems Society (HIMSS) 2012 data set categorizes eight application components as part of the category "electronic medical records." These application components are (i) clinical data repository (CDR), (ii) clinical decision support system (CDSS), (iii) computerized provider order entry (CPOE), (iv) physician documentation (PD), (v) order entry (OE), (vi) business intelligence–clinical, (vii) patient portal, and (viii) physician portal. However, Jha et al. (2009b) do not include the last three applications (or their equivalent functionalities) in their definition of EMRs. Moreover, HIMSS has changed its definition of EMR over time as health IT applications have evolved. Despite this apparent lack of consensus on what exactly constitutes EMRs, there is widespread agreement that CDR, CDSS, CPOE, and PD are part of EMRs (Dranove et al. 2014, Healthcare Information and Management Systems Society 2017, Atasoy et al. 2018). We briefly describe these vital EMR components:

CDR stores real-time data about individual patients, such as patient demographics, clinical information, hospitalization history, billing, and more.

CDSS assists providers in care decisions by providing reference information as well as suggestions for care. CDSS generates care suggestions by applying predefined rules to patient data (e.g., suggestions on drug-allergy contraindications for a specific patient).

CPOE enables providers to electronically add, change, store, and retrieve medication orders, laboratory orders, and radiology orders and receive decision support during these activities. Thus, CPOE enables communication, coordination, and consultation among providers, such as physicians, pharmacists, radiologists, and clinical laboratory physicians.

PD requires physicians to accurately record the diagnoses, symptoms, and other clinically relevant information during patient encounters. PD consolidates progress notes across hospital departments and, thus, enables communication between care providers (e.g., physicians and pharmacists). Physicians may receive decision support (e.g., help with correct diagnosis) while they are using PD.

Dranove et al. (2014) define *advanced EMR* as CPOE or PD, and we follow their definition to construct the focal variable for our study. We focus on advanced EMRs as the adoption of CPOE and PD has more variation than the adoption of CDR and CDSS for our study period, which starts in the year 2005. While basic EMRs, such as CDR and CDSS, may also improve patient safety, estimating their effects precisely for our study period is less likely, due to the lower variation in the adoption of basic EMRs.[2] In addition to this empirical rationale for our focus on advanced EMRs, we note that the advanced EMRs actually enable physicians to incorporate electronic decision support systems into their clinical workflows. For instance, an Agency for Healthcare Research and Quality (AHRQ) patient safety primer notes that "CPOE systems are generally paired with some form of clinical decision support system (CDSS), which can help prevent errors at the medication ordering and dispensing stages and can improve safety of other types of orders as well" (AHRQ Patient Safety Network 2017). CPOE also facilitates the use of patient order sets, which are evidence-based lists of orders for particular diagnoses. McCullough et al. (2016, p. 208) note that CPOE serves as a "platform for decision support functions, which may reduce prescribing errors and improve clinical guideline compliance."[3] PD also integrates with electronic decision support systems to reduce diagnostic errors. For example, PD integrated with decision support may warn a provider if the diagnosis of acute renal failure may be appropriate given the patient's serum creatinine level. Further, both CPOE and PD are critical sources of data on which accurate clinical decision support is based. In short, both CPOE and PD facilitate communication and coordination between care teams and enable the use of decision support by the providers. Practitioner anecdotes suggest that CPOE and PD are increasingly becoming indistinguishable because of the seamless

integration of these components.[4] This integration of CPOE and PD supports the definition proposed by Dranove et al. (2014), which we have adopted for this study.

2.2. Patient Safety

Great Britain House of Commons Health Committee (2009, p. 9) 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)." Patient safety events occur when patients are harmed or are exposed to the risk of harm resulting from medical care provided to them. The scope of patient safety events is broad—for example, patient safety events include "medication errors, communication problems in intensive care units (ICUs), gaps in the discharge process, and retained sponges in the operating room" (Wachter 2012, p. 3). In contrast, a patient safety event does not occur if the patient was treated correctly and the patient's condition deteriorated because of the natural progression of the disease. Section 3 discusses categorization of patient safety events based on the associated clinical processes.

Patient safety events may be assigned a harm category based on their severity. The severity of patient safety events varies substantially. In extreme cases, patient safety events may lead to the death of the patient. However, most patient safety events do not cause severe harm that result in permanent disability or death. Some patient safety events expose patients to the risk of harm but the patients are saved from harm because of timely intervention by providers or by chance. Such events are classified as "near misses" in the patient safety literature. Section 6.3 provides further discussion of patient safety events and their classification based on harm categories.

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, p. 1857) argued forcefully that many errors are preventable and many are "evidence of system flaws not character flaws." Patient safety events can and do occur under the medical care of competent and conscientious providers. Some of the reasons for patient safety events are the complexity of modern medicine, which creates cognitive overload; communication issues between providers; and transition and handoff issues during care. 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 unpreventable (Wachter 2012, pp. 3, 450).

As mentioned earlier, we further discuss patient safety events in Sections 3 and 6.3. Presently, we transition to a discussion of the measurement of patient safety events, a central issue in patient safety literature. There are three primary methods for identifying and measuring patient safety events, each with its own strengths and shortcomings when applied to epidemiological measurement:

(I) *Provider reporting systems* require care providers to report patient safety events to a common system, which may be internal to a hospital, such as the Johns Hopkins University's Intensive Care Unit Safety Reporting System (ICUSRS) (Holzmueller et al. 2005), or external, such as the PSA's Pennsylvania Patient Safety Reporting System (PA-PSRS). As of July 2017, a total of 28 U.S. states have implemented statewide provider reporting systems (Hanlon et al. 2015). These provider reporting systems may be voluntary or mandatory. For instance, PA-PSRS is a mandatory reporting system as we discuss in Section 4.1. Of the 28 U.S. states that have implemented patient safety reporting programs, 27 have implemented mandatory patient reporting systems. Oregon is the only state that has implemented a voluntary event-reporting program. Even in Oregon, a facility that joins Oregon's Patient Safety Reporting Program commits to reporting all events (Hanlon et al. 2015).

A big advantage of these event reporting systems is that they do not include false positives because the providers and the patient safety officers at the facility report the event after determining that the standard of care was found wanting. A disadvantage of these systems is that they may not include all events that took place. A common concern, somewhat unfounded, is that the providers would not be inclined to report the event for fear of medical liability claims. However, the legislation that establishes these event-reporting systems generally offers protection against use of the event-reporting data in medical liability cases. State courts have usually upheld these protections. For instance, the Iowa Supreme Court in a recent case upheld the confidentiality of a hospital's Patient Safety Net (PSN) documents and denied access to such documents to a patient who had filed a medical liability claim. The Supreme Court of Iowa (2017, p. 20) ruled that, "There is a strong public policy argument for interpreting section 135.42 broadly. The protection afforded by the confidentiality privilege allows hospital staff to feel comfortable reporting any and all safety concerns because those reports will remain confidential and not be subject to discovery in a legal proceeding. This confidentiality allows hospitals to utilize PSNs to reduce adverse patient safety events based on preventable medical errors."

(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 the AHRQ's PSIs (Wachter 2012). Although researchers

can construct PSIs from large administrative data sets, AHRQ and other experts have urged caution when using PSIs because these indicators are derived from administrative data rather than clinical data (Isaac and Jha 2008, Wachter 2012).

(III) *Trigger tools* are sets of defined rules to identify "trigger" events that may indicate iatrogenic injury. For instance, a patient who receives a dose of vitamin K or fresh frozen plasma may have received an overdose of the anticoagulant warfarin (Wachter 2012, p. 9). Thus, the administration of vitamin K may be considered a trigger event for warfarin overdose. However, not all trigger events may represent patient safety events. To determine whether a patient safety event occurred, highly trained analysts need to carry out a retrospective chart review (RCR). These RCRs, also known as medical record reviews (Vassar and Holzmann 2013), require analysts to review the patient's clinical data, such as diagnoses, tests, and provider notes, to ascertain if a patient safety event occurred. Thus, trigger tools entail high labor costs because of these RCRs. Moreover, trigger tools may generate too many alerts and may miss adverse events that have not been prospectively defined.

Trigger tools are a specific implementation of the general technique for detecting patient safety events by a comprehensive review of the patient's clinical records. A full chart review of all patients, in several hospitals over several years, by trained analysts to detect patient safety events would be prohibitively expensive. At a smaller scale, the Harvard Medical Practice Study has used chart reviews to capture patient safety events (Wachter 2012, p. 9). By requiring the occurrence of a trigger event for chart review, trigger tools reduce the number of charts to review.

A popular trigger tool is the Global Trigger Tool (GTT), developed by the Institute of Healthcare Improvement. Jha and Classen (2011, p. 1757) note that 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.

In this study, we have utilized data from the PSA's PA-PSRS, which is a mandatory provider reporting system. This study is among the first few that have compiled a comprehensive data set on medical errors as documented in PA-PSRS. This data set allows us to study the impact of EMRs from a different perspective than what the current literature has done. As the aforementioned discussion on patient safety measurement methods suggests, data from mandatory provider reporting systems, such as PA-PSRS, provide a good balance between accuracy and data-gathering costs across a large set of hospitals over several years when compared with the other methods for measuring patient safety.

2.3. Existing Literature on the Impact of Health IT on Patient Safety

Despite its importance, 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 suggests that the current literature is inconclusive because the studies are done on small samples, use unconvincing outcome measures, or do not use rigorous empirical methods (IOM 2011).

Aron et al. (2011) study two large Asian hospitals over three years to find that automation reduces medical errors. Although the medical informatics literature includes systematic reviews of small sample studies, such as Aron et al. (2011), the conclusions of these reviews are not definitive (Black et al. 2011).

Another challenge in the literature has been the lack of patient safety measures that are convincing to health policy makers and practitioners. For example, some studies have measured patient safety outcomes using the AHRQ's PSIs, which are inferred from billing data using AHRQ algorithms. As outlined in Section 2.2, AHRQ has urged caution in using PSIs. Further, the studies that use PSIs as outcome show mixed results. Parente and McCullough (2009) find a small beneficial effect of EMR on a few PSIs, and Menachemi et al. (2007) find beneficial effects of health IT. However, Culler et al. (2007) find no effects or harmful effects of health IT.

Although not directly studying patient safety events, a closely related 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 et al. (2016) 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 atherosclerosis, and pneumonia. They find that health IT improves outcomes for the most severe cases but does not reduce mortality for the median patient. Our study differentiates from this literature stream in the following ways: (I) We study the impact of EMRs on both fatal and nonfatal errors as the PSA's PA-PSRS data classifies events by their severity. Although mortality is an important healthcare measure, using mortality as the only outcome measure does not capture the broader impact of EMRs on a variety of errors that do not lead to death; nonfatal errors also inflict significant human and economic consequences and are more frequent than fatal errors. (II) Our data covers patients of all ages and disease conditions, and thus, allows us to unpack the impact of EMRs on patient safety events more generally. (III) Patient safety events (resulting from medical errors) in our data are further split

into various subcategories, such as medication errors, skin integrity errors, and so on. Thus, we can examine the impact of EMRs at a more granular level.

In summary, while the existing literature has provided some answers, the question of advanced EMRs' impact on patient safety is far from settled as concluded by the IOM (2011) report. Our paper not only estimates the overall impact of advanced EMRs on patient safety events, but also breaks down the effect by the clinical processes that led to the error as we discuss in Section 3. Moreover, our study period is more recent (2005–2014), we include patient safety events across all ages and disease types, and we source the patient safety event data from a mandatory patient safety reporting system. As prominent Johns Hopkins physician and patient safety expert Peter Pronovost acknowledges (Pronovost et al. 2008), the Institute of Medicine has recommended using patient safety reporting systems (PSRS) (Brennan et al. 2004, Aspden et al. 2004), which has led to a large number of states enacting legislation that mandates patient safety reporting systems as we discussed in Section 2.2. We fill a gap in the literature by basing our study on patient safety measures that are increasingly being adopted across the United States.

3. Clinical Processes, Medical Errors, and EMRs

Modern medicine is extremely complex. There are more than 14,000 different diagnoses (see World Health Organization 2013, 14,199 codes in ICD-10), more than 6,000 drugs, and more than 4,000 medical and surgical procedures. The sheer number of diagnoses, drugs, and procedures produces cognitive overload that may lead to errors even by competent, caring, and conscientious care providers. EMRs can reduce errors because they "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, p. 2526). Thus, the medical community expects that advanced EMRs are likely to have high clinical impact (Jha et al. 2009b, 2010).

The Pennsylvania patient safety data set categorizes events according to an event taxonomy. The primary event categories are (i) medication error; (ii) error related to procedure, treatment, and/or test (error PTT); (iii) complication of procedure, treatment, and/or test; (iv) fall; (v) skin integrity; (vi) other and/or miscellaneous; (vii) adverse drug reaction (not a medication error); (viii) equipment, supplies, and/or devices; and (ix) transfusion.

This disaggregation by event categories allows deeper study as we can link advanced EMRs' effect on patient safety through their impact on different clinical processes. Patients receiving care at the hospital are subject to various clinical processes, such as physician encounter, diagnostic testing, medication prescription and administration, procedures, and other treatments. For example, a patient safety event, such as postoperative bleeding, may occur because of error in surgical procedure, error in medication, or error in diagnosis. To elaborate, postoperative bleeding may be (i) a complication of procedure, treatment, and/or test if the surgeon did not suture the blood vessels properly; (ii) a medication error if the providers improperly withheld antiplatelet therapy, such as Plavix; or (iii) an error related to procedure, treatment, and/or test (error PTT) if the providers missed during diagnosis that the patient is genetically predisposed to bleeding. Using postoperative bleeding as the outcome variable aggregates the clinical processes that actually drive this condition. With data disaggregated into appropriate categories, it would be possible to distinguish if bleeding occurred because of medication, complication, or procedure errors. Hence, by using disaggregated data, we can gain deeper insights into how EMRs affect patient safety and what it means to hospitals adopting EMRs.

Advanced EMRs are expected to benefit clinical processes associated with some of these error categories but not all. We will discuss these event categories and the expected impact of advanced EMRs on these categories presently.

3.1. Medication Errors

In the PSA data set, the subcategory "medication errors" aggregates 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 the impact of advanced EMRs on medication errors, not only because of the high volume and cost of medication errors, but also because medication errors conceptually seem amenable to improvements through the use of advanced EMRs. In general, clinical literature suggests that advanced EMRs may beneficially impact medication errors, whose "prevention is a worldwide priority for health systems" (Agrawal 2009, p. 681).

Bates et al. (1995) found that most of the medication-related patient safety events occurred at the ordering stage. The findings reported by Bates et al. (1995) have been used to advocate the adoption of CPOE (AHRQ Patient Safety Network 1995) as "these errors had a variety of causes, including poor handwriting, ambiguous abbreviations, or simple lack of knowledge on the part of the ordering clinician," and a CPOE system could prevent patient safety events "at the ordering and transcribing stages by (at a minimum) ensuring

standardized, legible, and complete orders" (AHRQ Patient Safety Network 2017). In summary, CPOE can reduce medication errors by alleviating communication issues (legibility; drug name confusion; confusion between metric and apothecary units; specification errors, such as trailing zeros), shortening transmission time and completion time, and enabling "correct" ordering by making it easier to integrate with patient data and clinical decision support (Wachter 2012, p. 211). In addition, physician documentation can also contribute to reducing medication errors. For instance, 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 PD can impact medication errors. First, 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. 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 of the redundant and error-prone steps. Moreover, the order is available almost instantaneously to the pharmacist, potentially reducing errors resulting from delays in administering the drug.

Second, for certain prescriptions, the pharmacist may need additional information about patient indications to correctly administer the drug. For example, the anticoagulant 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 it is administered subcutaneously for prevention of clots. To determine whether heparin is prescribed for prevention or treatment when the hospital has not yet implemented PD, would be cumbersome even for a floor pharmacist as the pharmacist might have needed access to the patient's paper charts. For after-hours pharmacists (in a central location), though, getting access to paper charts would be more cumbersome and more likely to cause errors. With the adoption of PD at the hospital, both floor and after-hour pharmacists can now easily check physician notes to determine the correct route of administration.

Based on the suggestions in the clinical literature and the brief discussion in this subsection, we expect advanced EMRs to contribute to a reduction in medication errors.

3.2. 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. 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 electrocardiogram (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 et al. 2011).

3.3. Error Related to Procedure, Treatment, and/or Test (Error PTT)

The subcategory "error PTT" 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. Advanced EMRs 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 accurate ordering of the required medical tests, correct identification of patients, and appropriate scheduling of the tests.

3.4. Fall

The subcategory "fall" tracks all hospital patient falls, which are defined as "unplanned descent to the floor with or without injury to the patient" (AHRQ 2013). Commonly observed injuries from falls are fractures, lacerations, and internal bleeding. Fall risk factors include problems with walking and transfers, patients' mental confusion, frequent toileting needs, and (crucially) medication side effects (AHRQ 2013). For some of these fall risk factors, EMRs may only have a marginal indirect impact. However, EMRs may substantively contribute in preventing falls through better management of medications. Among the fall risk factors, medications, such as antipsychotic medications, hypnotic medications, diuretic medications, anticoagulants, opioid analgesics, anticonvulsants, antihypertensive medications, and hypoglycemic agents (including insulin), are recognized as fall risk factors (Weber et al. 2008, AHRQ 2013, Marier et al. 2016, Centers

for Disease Control 2016). In addition, polypharmacy, which is the "effects of taking multiple medications concurrently to manage coexisting health problems" (Woodruff 2010), can increase fall risk. EMRs can help mitigate these fall risks. Marier et al. (2016) found that using EMR data, which is more frequently updated than other, paper-based information sources, would improve the ability to identify those at risk for falls in nursing homes. Centers for Disease Control (2016) describes the successful integration of the fall risk assessment algorithm into the EMR at a Oregon Health and Science University clinic starting in 2011. Weber et al. (2008) found that using EMRs to assess medication use reduced falls in an ambulatory elderly population in central and northeastern Pennsylvania. Thus, EMRs can reduce the incidents of falls through better medication management as well as through a reduction in medication errors.

3.5. Skin Integrity, Equipment, Transfusion, Adverse Drug, and Miscellaneous Events

For a number of subcategories, no impact of EMR is expected. These subcategories are (I) "adverse drug reactions (not a medication error)," which include physiologic reactions to drugs, such as skin reactions (e.g., hives), hypotension, arrhythmia, nephrotoxicity, or mental status change. We emphasize that these adverse drug reactions were deemed to be *not medication errors*; medication error–related drug reactions are categorized as medication errors in the PSA data. (II) "Equipment/supplies/devices" include medical device malfunctions, electrical problems, broken or outdated devices or components, equipment misuse, and lack of availability. (III) "Transfusion" includes hemolytic reactions, errors in blood product component or patient requested or issued, problems with sample collection or storage, and problems with distribution. (IV) "Miscellaneous" includes inappropriate discharge, restraints, and elopement. (V) "Skin integrity" events include pressure ulcers, venous stasis ulcers, burns, rashes, hives, abrasions, lacerations, blisters, and skin tears.

It is intuitively obvious that some of these subcategories, such as "equipment/supplies/devices" errors, would not be affected by advanced EMRs. For the other subcategories, the patient safety experts at PSA do not expect EMRs to have an impact on these subcategories. For instance, the subcategory adverse drug reactions records events that are not medication errors because the adverse reaction was unexpected and not something caused by the providers by ignoring patient information or not following the proper medical protocol. As yet another example, the skin integrity events are caused by problems with patient positioning, movement, or manipulation; physical environment; or use of devices near or on patients. Thus, it is reasonable to assume that skin integrity events are not affected by advanced EMRs—an assumption we have informally validated with patient safety experts and physicians.

In summary, these subcategories—skin integrity, equipment, transfusion, adverse drug, and miscellaneous events—are not expected to be impacted by advanced EMRs. Thus, we can use these subcategories as placebo outcomes to test the robustness of the estimated effect of advanced EMRs on all events and the categories that are expected to benefit, such as medication events.

4. Data Sources and Variable Construction

We construct an unbalanced panel for Pennsylvania hospitals over 2005–2014 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); (iv) transfer-adjusted case mix index control, published by Centers for Medicare and Medicaid Services (CMS), is sourced from the National Bureau of Economic Research; and (v) location-specific controls are sourced from the Area Health Resources Files (AHRF).

4.1. 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 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 in 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 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 because 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 per day. To promote reporting by providers, MCARE provides assurances 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. Although 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 PA-PSRS data set, which includes all events reported from January 1, 2005, to December 31, 2014. For this 10-year period, the data set has 236 unique Pennsylvania hospitals though the number of hospitals varies by the year. These hospitals reported approximately 2.1 million events over 10 calendar years, classifying events into nine primary categories. These primary categories are further modified by several secondary and tertiary subcategories. The PA-PSRS is based on a taxonomy developed by the University HealthSystems Consortium (UHC) Patient Safety Net (PSN) and modified to meet the requirements of the MCARE Act. The use of these event categories for coding facilitates analysis that leads to a deeper understanding of the context and drivers of patient safety events. The primary event categories are (i) error related to procedure, treatment, and/or test (error PTT), (ii) medication error, (iii) fall, (iv) skin integrity, (v) complication of procedure, treatment, and/or test (complication PTT), (vi) other and/or miscellaneous, (vii) adverse drug reaction (not a medication error), (viii) equipment, supplies, and/or devices, and (ix) transfusion. We describe these categories in a later section.

Table 1 provides descriptive statistics on patient safety events—roughly 1,000 events were reported on average (by hospital-year), with error PTT, medication errors, and falls being the top three primary event categories. Figure 1 shows a net increasing time trend for total number of events—roughly 165,000 events were reported in 2005, which increased to roughly 230,000 events in 2014.

Table 1. Summary of Reported Patient Safety Events for Pennsylvania Hospitals, 2005–2014

	Mean	SD	Total
All events	973	(1,391)	2,122,531
Error PTT	220	(443)	479,973
Medication	206	(452)	449,250
Falls	156	(213)	340,112
Skin integrity	134	(289)	293,079
Complication PTT	133	(249)	290,251
Other or miscellaneous	73	(150)	158,289
Adverse drug reaction	20	(46)	44,299
Equipment	18	(48)	38,903
Transfusion	13	(35)	28,375

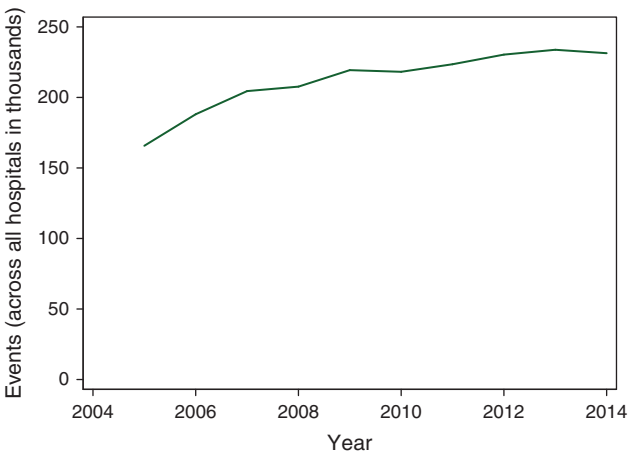
Notes. This table provides a summary for events reported by hospitals to the Pennsylvania Patient Safety Authority during years 2005–2014. The unit of analysis is hospital-year. Columns "Mean," "SD," and "Total" report the average, standard deviation, and total events for the category, respectively. Where applicable, numbers are rounded to integers.

4.2. 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 hospitals 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 2014). 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

Figure 1. Reported Patient Safety Events for Pennsylvania Hospitals, 2005–2014



population older than 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 EMR effect literature (e.g., Dranove et al. 2014) in including these location-specific controls to model time trends.

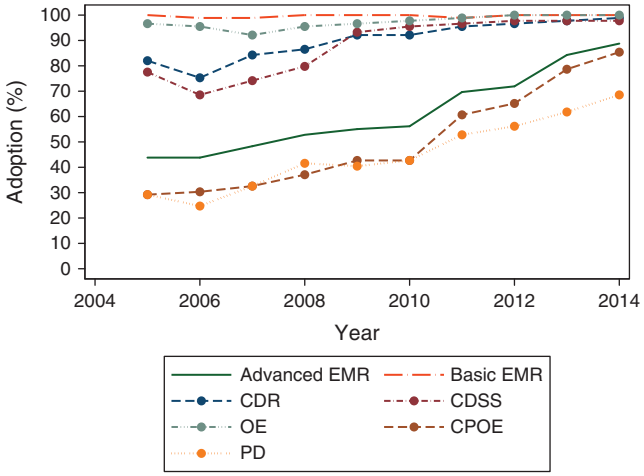
4.3. HIMSS Health IT Data and the Combined Data Set

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 U.S. 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 (Parente and McCullough 2009, Miller and Tucker 2011, Dranove et al. 2014, McCullough et al. 2016).

We use HIMSS data from the years 2005–2014 to construct EMR adoption measures. For most hospitals, HIMSS directly reports the hospital's adoption of CDR, CDSS, OE, CPOE, and PD. We define the year of adoption of the particular EMR component as the year after the first year when a specific hospital reported a status of "live and operational." The rationale for this definition is as follows: 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 the 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 variable by closely following the definition provided by Dranove et al. (2014): *Advanced EMR* is defined as the adoption of CPOE or PD. Figure 2 plots the adoption trend for advanced EMRs as well as other EMR components. During the study period (2005–2014), there is little variation in the adoption of basic EMR, which is defined by Dranove et al. (2014) as the adoption of CDR or CDSS or OE. To increase variation, we use CDR, CDSS, and OE as separate control variables in our models rather than using the basic EMR construct. In contrast to the low variation in basic EMR adoption, about 47% Pennsylvania hospitals adopted advanced EMR during the study period.

Figure 2. (Color online) EMR Adoption Trend at Pennsylvania Hospitals



Our final data set is a combination of data from AHA, AHRF, HIMSS, PHC4, and PSA. Table 2 compares variable averages for hospitals with or without advanced EMR in 2005. Adopter hospitals are larger, more likely to be members of the Council of Teaching Hospitals, and are located in larger counties. These sample characteristics are consistent with the sample characteristics reported by Dranove et al. (2014).

As our data set is drawn from Pennsylvania, we now present some basic facts about Pennsylvania, followed by a comparison of our sample averages to national averages. Pennsylvania is the sixth largest U.S. state by population and the sixth largest state economy. Its population was estimated to be 13 million in 2011 and its gross state product was valued at $580 billion in 2010 (Pennsylvania State Data Center 2013). Table 3 compares Pennsylvania sample averages to national averages.[7] Compared nationally, Pennsylvania hospitals are slightly larger and are more likely to be members of the

Table 2. Comparing Hospitals With and Without Advanced EMR in 2005

Variable	With	Without
Hospital Size (patient days)	65,556	55,064
Teaching Hospital	0.26	0.13
Residency Program	0.4	0.3
Med School Affiliation	0.53	0.33
Joint Commission Accreditation	0.91	0.84
Population (county)	662,686	486,699
Percent Over 65 (county)	0.15	0.16
Percent White (county)	0.8	0.9
Median Household Income (County)	40,104	42,359
Unemployment (county)	6.1	5.8

Notes. Columns "With" and "Without" report variable means for hospitals with or without advanced EMR in 2005. Where applicable, numbers are rounded to integers.

Table 3. Comparing National and Pennsylvania Sample Hospital Characteristics

Variable	National	Pennsylvania
Hospital Size (patient days)	38,044	49,699
Transfer-Adjusted Case Mix Index	1.3	1.4
Teaching Hospital	0.058	0.15
Residency Program	0.17	0.29
Medical School Affiliation	0.23	0.34
Joint Commission Accreditation	0.73	0.82
CPOE (percent adoption in 2005)	18	28
Physician Documentation (percent adoption in 2005)	19	25
Advanced EMR (percent adoption in 2005)	32	41
CPOE (percent adoption in 2014)	85	86
Physician Documentation (percent adoption in 2014)	73	69
Advanced EMR (percent adoption in 2014)	88	88

Council for Teaching Hospitals. However, the average case mix seems to be similar for both samples. While hospitals in our sample had slightly higher advanced EMR adoption in 2005, the advanced EMR adoption rates for Pennsylvania hospitals were almost identical to national adoption rates by 2014.

Pennsylvania's patient safety reporting has influenced patient safety reporting in other U.S. states. The mandatory patient safety reporting law went into effect in Pennsylvania in 2004. By July 2017, 28 states have implemented mandatory patient safety event reporting systems (Pronovost et al. 2008, Hanlon et al. 2015). The Pennsylvania Patient Safety Authority's PA-PSRS is the nation's largest and one of the most recognized statewide patient safety databases. Regarding Pennsylvania's mandatory reporting system (and Maine's Sentinel Event Reporting Program), the Department of Health and Human Services reported in the comment section of the Final Rule on the Patient Protection and Affordable Care Act's (ACA) Benefit and Payment Parameters for 2017: "these State-level reporting programs are robust, evidence-based, effective patient safety programs that have delivered high value and improved patient safety across their regions" (Department of Health and Human Services 2016).[8]

5. Models and Identification

To identify the effect of advanced EMRs on patient safety, we use the difference-in-differences (DID) method. Our panel data set enables the DID method because almost half of the hospitals in our sample adopted advanced EMRs during the study period as shown in Figure 2.

Our unit of analysis is hospital-year, and we have annual data from 2005 through 2014. The focal variable for identification is the adoption of advanced EMR whereas the observed outcome is the number of patient safety events at a hospital in a particular year. In our models, we use the natural logarithm of patient safety events as the dependent variable. We also control for hospital size, hospital fixed effects, year fixed effects, teaching-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):

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

where i denotes hospital, and t denotes time (year).

In an "ideal experiment," the hospitals' adoption of advanced EMRs would be independent random events. Our study differs from this ideal setup because hospitals' adoption of advanced EMRs is not entirely random. The medical informatics literature suggests that most hospitals' adoption decisions are associated with hospitals' size, urban versus rural location, and teaching versus nonteaching status (Jha et al. 2009a, 2010; Abraham et al. 2011; DesRoches et al. 2012). These factors are also likely to be correlated with patient safety events. For example, a univariate regression of log of patient safety events on log of hospital size (not presented here) suggests that a 1% in increase in hospital size is associated with a 0.7% increase in patient safety events. Thus, it is likely that larger hospitals, on average, have higher patient safety events.

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 over the study period is likely to be small because patient flow is largely determined by exogenous factors. Thus, we are not concerned that hospital size is an intermediate outcome that should not be controlled. On the other hand, we are concerned that omitting hospital size may bias our estimates.

We also include hospital-level binary controls, such as hospital's accreditation with The Joint Commission, hospital's affiliation with a medical school, hospital's offer of a residency program, and hospital's membership in the Council of Teaching Hospitals and Health Systems (COTH). 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, time-invariant hospital characteristics will be differenced out. However, baseline values for these hospital-level controls can be used to include flexible time trends. Following Dranove et al. (2014), we include linear time trend interacted with these hospital characteristics. However,

Table 2 shows that COTH membership averages differ substantially for hospitals with or without advanced EMRs in 2005, so we include teaching-year fixed effects to further strengthen our model. COTH membership, medical school affiliation, and residency program are highly (positively) correlated so it suffices to control for teaching-year fixed effects. Our models also 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 older than 65, percentage of population that is white, percentage of population that is unemployed, and the median household income.

Despite this extensive set of controls, there may still be a concern that hospitals' event reporting changes with advanced EMR adoption. The PSA patient safety experts, who work closely with hospital patient safety organizations (PSO), have maintained that a particular hospital's reporting culture depends on the hospital PSO staff and policies. The hospitals' PSO policies are, in turn, driven primarily by PSA requirements and have generally remained stable over the study period. The increased reporting observed in Figure 1 is a result of an increase in general awareness about patient safety. The increased awareness is a result of PSA's statewide patient safety educational webinars and patient safety advisories (and similar common shocks at the national level). These common shocks are controlled for in a DID design. Hence, hospital and year fixed effects unconfound reporting culture. Even then, we use hospitals' implementation of an electronic patient safety event reporting interface as an additional control to proxy for hospitals' reporting culture.[9] Another concern could be that hospitals with relatively more severe case mixes may have higher rates of patient safety events. Hospital case mix is also relatively stable over time and thus unconfounded by hospital fixed effects in our models. For our main analysis in Section 6, we assume that the controls in specification (1) unconfound the hospitals' adoption of advanced EMRs. However, in Section 7, we explore the robustness of our results by explicitly controlling for other variables, such as the transfer-adjusted case mix index.

Further, our identification through a DID design depends on the assumption that hospitals in the treatment and control group have similar time trends. An absence of similar time trends would be a threat to the validity of our results. Another threat to the validity of our identification would be reverse causality (i.e., patient safety events driving the adoption of advanced EMRs rather than the other way around). A number of robustness checks have been used in the literature (Autor 2003, McCrary 2007, Agha 2014) to address these concerns. We report these robustness checks in Sections 6.1 and 7.

Another well-known issue with DID design is correct calculation of standard errors for valid inference. Hospital outcomes across years are likely to be serially correlated and the default standard errors would be downward-biased. To avoid this downward-bias of the default standard errors, we follow advice from Bertrand et al. (2004) and estimate robust standard errors with clustering on hospitals. Our estimated standard errors are robust to heteroskedasticity and serial correlation.

6. Results

6.1. Effect of Advanced EMRs on All Patient Safety Events

Table 4 presents results from estimating variants of specification (1). We start with a parsimonious DID specification in column (1) in which we control for hospital fixed effects, year fixed effects, and hospital size (through Log *Patient Days*). Column (2) adds controls for CDR, CDSS, OE, country characteristics interacted with year. Column (3) further adds a control for the PSA eReporting interface. Column (3) is our preferred

Table 4. EMR Adoption and All Patient Safety Events

	(1) b/se	(2) b/se	(3) b/se	(4) b/se
Advanced EMR (AEMR)	−0.217** (0.109)	−0.192* (0.108)	−0.193* (0.108)	−0.183* (0.107)
CDR		−0.026 (0.127)	−0.024 (0.127)	−0.027 (0.127)
CDSS		−0.059 (0.114)	−0.057 (0.112)	0.000 (0.108)
OE		−0.049 (0.129)	−0.048 (0.129)	−0.081 (0.129)
PSA eReporting Interface			0.055 (0.160)	0.038 (0.154)
Log *Patient Days*	0.093 (0.202)	0.074 (0.194)	0.071 (0.194)	69.659 (54.142)
(Log *Patient Days*) × *Year*				−0.035 (0.027)
Hospital controls × Year	Yes	Yes	Yes	Yes
Teaching-year fixed effects	Yes	Yes	Yes	Yes
County controls × Year	No	Yes	Yes	Yes
Never-adopter-year fixed effects	No	No	No	Yes
Always-adopter-year fixed effects	No	No	No	Yes
Hospital and year fixed effects	Yes	Yes	Yes	Yes
Variance-covariance estimator	Robust	Robust	Robust	Robust
Panel size	166	166	166	166
Observations	1,248	1,248	1,248	1,248
AEMR effect (percent change)	−19.5	−17.4	−17.5	−16.7

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

DID specification, and the results in Section 7.2 further justify this choice.

Column (4) presents a robustness check with more flexible time trends similar to the check by Agha (2014) for her main outcome.[10] Specifically, we include year fixed effects for nonadopter and always-adopter hospitals in column (4). These fixed effects allow nonadopter hospitals and always-adopter hospitals to trend differently from the hospitals that adopted during the study period.[11] We also allow hospitals to trend differently by size by including an interaction between *Year* and Log *Patient Days* (which measures hospital size). Because hospital size is mostly unique to the hospital, this time trend allows hospitals to trend differentially.[12] Column (4) shows that the results are robust to the inclusion of these flexible time trends. The estimated effect size and their standard error is similar to the result of our preferred specification in column (3).

Table 4 shows that the coefficient estimates for advanced EMRs range from −0.183 to −0.217. The last row in Table 4 reports the percent change in patient safety events resulting from the adoption of advanced EMRs. These percent changes are calculated using the formula $100 * (e^{\beta_2} - 1)$, where β_2 is the coefficient for advanced EMR. Column (3), the preferred specification, shows a 17.5% decline in patient safety events attributable to hospitals' advanced EMR adoption.[13]

The estimates for the hospital size and PSA eReporting interface controls are in the expected direction although these estimates lack precision. The point estimates for basic EMR applications—CDR, CDSS, and OE—suggest either a small reduction or no reduction in patient safety events although these estimates are statistically not significant. In particular, the coefficient for CDSS ranges between −0.057 and 0, which suggests either a small reduction or no effect in patient safety events resulting from CDSS. However, these estimated CDSS coefficients have large standard errors. Although decision support is expected to improve patient safety, its estimates lack precision because hospitals in our data set have low variation for CDSS adoption. Also, the benefits from CDSS largely accrue through its use via CPOE. For instance, a Congressional Research Service (CRS) study attributes a decision support function to CPOE by noting that CPOE systems "allow physicians to order medications electronically and *alerts them to possible prescribing errors*" (Fernandez and Larkins 2005).[14] The second functionality—alerting physicians to possible prescribing errors—is a decision support function, but the physicians use it through CPOE. We do not discuss these basic EMR systems further in this paper and instead focus on the advanced EMR systems, CPOE and PD.

6.2. Effect of Advanced EMR on Events by Clinical Categories

In Section 3, we discussed various event categories and the expected impact of advanced EMR on patient safety events in those categories. The results of analysis by these event categories are presented in Table 5.

Table 5. EMR Adoption and Events by Clinical Categories

	(1) Med b/se	(2) Comp b/se	(3) Proc b/se	(4) Fall b/se	(5) Skin b/se	(6) Adv b/se	(7) Equip b/se	(8) Trans b/se	(9) Misc b/se
Advanced EMR (*AEMR*)	−0.243**	−0.182*	−0.145	−0.196**	0.001	−0.023	0.034	−0.042	0.082
	(0.101)	(0.105)	(0.118)	(0.083)	(0.109)	(0.099)	(0.109)	(0.093)	(0.134)
Log *Patient Days*	0.058	0.087	−0.398	0.669**	0.190	−0.044	−0.114	−0.185	0.026
	(0.199)	(0.245)	(0.275)	(0.281)	(0.254)	(0.306)	(0.330)	(0.229)	(0.249)
CDR	0.019	−0.015	−0.251	0.053	0.155	0.065	−0.046	0.006	0.145
	(0.107)	(0.129)	(0.172)	(0.107)	(0.145)	(0.142)	(0.145)	(0.118)	(0.184)
CDSS	−0.067	−0.097	−0.222*	−0.052	0.118	0.133	−0.138	−0.056	−0.125
	(0.123)	(0.117)	(0.133)	(0.114)	(0.150)	(0.141)	(0.135)	(0.120)	(0.162)
OE	−0.088	0.012	−0.187	0.053	−0.204	−0.022	−0.231	−0.103	−0.156
	(0.151)	(0.113)	(0.197)	(0.125)	(0.136)	(0.140)	(0.140)	(0.120)	(0.171)
PSA eReporting Interface	0.143	0.313*	0.121	−0.154	−0.027	0.050	0.072	0.116	0.394**
	(0.163)	(0.176)	(0.206)	(0.138)	(0.158)	(0.131)	(0.162)	(0.135)	(0.193)
County controls × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teaching-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Variance–covariance estimator	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Panel size	166	166	166	166	166	164	164	156	165
Observations	1,222	1,248	1,248	1,238	1,248	1,057	1,063	1,034	1,189
AEMR effect (percent change)	−21.6	−16.6	−13.5	−17.8	0.1	−2.3	3.5	−4.1	8.6

Note. Standard errors are calculated using cluster-robust variance–covariance estimator.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

These results break down the overall impact by focusing on clinical processes that may or may not be impacted by advanced EMRs. Thus, these results provide further insights into the processes through which advanced EMRs are affecting the overall patient safety at Pennsylvania hospitals.

In addition to presenting the coefficient estimates, the last row of Table 5 also presents the percent change in patient safety events by clinical categories to facilitate discussion. Column (1) shows that medication errors decline by 21.6% because of advanced EMR adoption. Thus, as expected, we find a large improvement in medication errors attributable to advanced EMRs. Similarly, column (2) shows that complications decline by 16.6% because of advanced EMR adoption. Although column (3) shows that "errors in procedure, treatment, or test" (error PTT) decline by 13.5% because of advanced EMR adoption, the estimates are not statistically significant at the 10% level. Finally, column (4) shows that falls declined by 17.8% because of advanced EMR adoption.

Table 5, columns (5)–(9) present the results for the remaining subcategories. The effect sizes are comparatively small in magnitude and statistically insignificant. For instance, Table 5, column (5) reports the results for skin integrity events. The estimated effect for skin integrity is directionally opposite and statistically not significant. The results for these placebo outcomes (columns (5)–(9)) suggest the robustness of the estimated results and reassure us that there was no contemporaneous change (e.g., changes in other processes that affect safety) in hospitals when they implemented EMRs.

6.3. Effect of Advanced EMR on Events by Harm Categories

Previous analysis does not provide insights into the severity of errors. Prior literature, for example, has measured the impact of EMRs on mortality only. The PSA patient safety events have a designated harm score, which indicates the severity of the event and reflects the subsequent human and economic costs. These harm scores allow us to analyze events by their severity. Using the reported harm scores, events can be grouped into three categories: (i) adverse events, which have the highest severity; (ii) reached patient events, which have medium severity; and (iii) near miss events, which have the lowest severity. Table 6 shows a brief description of these categories and the number of events in each category. These event categories allow us to examine the impact of advanced EMRs by the severity of events. Table 7 shows the estimates for specification (1) except that the measured outcomes are the number of events in each of these harm categories.

For columns (1)–(3) in Table 7, the dependent variable is the sum of all event types by harm categories (near miss, reached patient, adverse events). The effect of advanced EMR on reached patient events is substantive—a statistically significant 19.2% decline. The estimated effects on adverse events and near misses also suggest declines of 6% and 7% respectively, but the standard errors for these estimates are large.

However, as discussed earlier in Sections 3 and 6.2, not all event types are expected to benefit from advanced EMRs. In Section 3, we discussed why we expect medications, complications, procedures, and falls (and not the other subcategories) to be impacted by advanced EMRs. Table 5 in Section 6.2 presented results by clinical categories, and it was shown there that medication errors, complications, and falls have statistically significant declines. Although the effect on procedure errors was substantive, it was not statistically significant. Thus, columns (4)–(6) further analyze medication errors, complications, and falls, disaggregated by harm score.[15]

For columns (4)–(6) in Table 7, the dependent variable is the sum of medication, fall, complication events disaggregated by the harm categories. The null result for the near miss harm category for all events persists for these three event subcategories too. However, the impact of advanced EMRs on the adverse event category is a statistically significant reduction of 16.2%. Furthermore, compared to the earlier result with all events, the effect on medication, fall, and complication events in the reached patient category shows a larger decline of 22.5% and improved precision.

Table 6. Count of Patient Safety Events by Harm Categories

Category	Severity	No. of events	Description
Adverse events	High	63,176	Event resulted in patient harm, including death in extreme cases (resulting in both human and economic costs)
Reached patient events	Medium	1,555,131	Event reached patient but did not cause patient harm. However, patient may have required increased monitoring or medical intervention (resulting in both human and economic costs)
Near miss events	Low	504,224	Event did not reach patient either by chance or through active recovery effort by caregivers (resulting in an economic cost)

Note. Description based on content from the National Coordinating Council for Medication Error Reporting and Prevention.

Table 7. EMR Adoption and Events by Harm Score—Near Misses, Reached Patients, and Adverse Events

	(1) Near miss (within all events) b/se	(2) Reached patient (within all events) b/se	(3) Adverse events (within all events) b/se	(4) Near miss (med, comp, fall only) b/se	(5) Reached patients (med, comp, fall only) b/se	(6) Adverse events (med, comp, fall only) b/se
Advanced EMR (AEMR)	−0.073	−0.214*	−0.062	−0.186	−0.254**	−0.177**
	(0.142)	(0.129)	(0.077)	(0.145)	(0.125)	(0.079)
Log *Patient Days*	−0.089	0.056	0.339	0.006	0.180	0.532*
	(0.280)	(0.220)	(0.271)	(0.297)	(0.232)	(0.274)
PSA eReporting Interface	0.280	−0.019	0.048	0.326	0.009	−0.019
	(0.238)	(0.170)	(0.090)	(0.246)	(0.165)	(0.091)
Basic EMR	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls × Year	Yes	Yes	Yes	Yes	Yes	Yes
Teaching-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County controls × Year	Yes	Yes	Yes	Yes	Yes	Yes
Hospital and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Variance-covariance estimator	Robust	Robust	Robust	Robust	Robust	Robust
Panel size	166	166	166	166	166	166
Observations	1,248	1,248	1,248	1,248	1,248	1,248
AEMR effect (percent change)	−7.0	−19.2	−6.0	−17.0	−22.5	−16.2

Notes. Standard errors are calculated using cluster-robust variance–covariance estimator. For columns (1)–(3), all event types are aggregated by harm categories. For columns (4)–(6), medication, fall, and complication event types are aggregated by harm categories.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Thus, our results suggest that advanced EMRs have a significant impact, but much of the impact is concentrated around medication, fall and complication errors. Within these categories, the impact is large and affects events at all severity levels. This decline reduces unnecessary monitoring and medical interventions and has likely led to large cost savings for Pennsylvania hospitals. We discuss the economic impact of error reduction in a later section.

7. Robustness

Given that our study uses a DID research design, the identification depends on a common trend assumption for the treated and nontreated groups. In addition, we assume that the explicit controls, hospital fixed effects, and year fixed effects unconfound the adoption of advanced EMR. In this section, we explore the robustness of our results by probing around these assumptions. Specifically, we investigate the robustness of our results in the following ways: (i) we examine whether our results are robust to nonclinical IT and case mix index (CMI) as additional controls, (ii) we estimate the dynamic effects of advanced EMRs using leads and lags of advanced EMR adoption to compare trends at the treated and control hospitals.

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

7.1. Robustness to Nonclinical IT and Case Mix Index as Additional Controls

First, we investigate the robustness of our main results by introducing two additional controls—hospital's use of nonclinical IT and hospital's CMI. The rationale for including nonclinical IT controls is as follows. It is plausible that hospitals with increasing IT sophistication may also have increasing clinical quality. Although hospital fixed effects control for the time-invariant portion of IT usage of the hospital, we can capture the variation in hospital's IT ability through changes in nonclinical IT applications. Hospitals use a variety of nonclinical IT applications that do not directly impact patient safety events. In the HIMSS data set, these nonclinical applications are aggregated into categories, such as general financials, human resources, revenue cycle management, and supply chain management. We use the reported adoption of these nonclinical IT systems to proxy for IT changes at the hospital.[16] We now discuss the rationale for including CMI as additional control. Although originally intended for use in billing, CMI has become an indicator of severity of a hospital's patient population (Mendez et al. 2014). In our main analysis, we assume that the average severity of hospitals' patients is unconfounded by hospital fixed effects. This assumption is plausible because the average severity of hospital's patient population is relatively stable over time. As an additional check, we explore the validity of our main results by explicitly controlling for the hospitals' transfer-adjusted case mix index (CMI). The CMI data is published by the Centers for Medicaid and Medicare Services and is archived for the study period at the National Bureau of Economic Research. We did not include this control in our main analysis because the CMI data for several hospitals is unavailable, such that we end up with more than 10% of our observations

with missing CMI values.[17] In our robustness analysis here, we use predicted values for observations with missing CMI values. For prediction, we first estimate a linear regression model of observed CMI on hospital characteristics, county characteristics, and year dummies. We then predict the missing CMIs using our estimated linear model and use a combination of the reported CMI values and our estimates of the missing CMI values to control for the average severity of hospital's patients while estimating the model in specification (1).

When we reestimate specification (1) with these additional controls, the results are similar to the main results presented earlier—the estimated coefficient for advanced EMRs is −0.202 ($SE = 0.117$) when the dependent variable is all events and −0.291 ($SE = 0.103$) when the dependent variable is medication events.[18]

7.2. Dynamic Effect of Advanced EMR on Patient Safety

The DID identification in this study depends on two assumptions: (i) the treated and control hospitals have common time trends and (ii) that adoption of advanced EMRs impacts patient safety events and not vice versa (no reverse causality). For a DID design, it is easier to visually compare trends if all treated units receive treatment at the same time but much harder if treated units receive treatment at different times. As hospitals in our study adopt EMRs at different times, it is difficult to directly compare the trends of the treated and control groups. However, we can carry out a dynamic effects analysis similar to the analysis in Autor (2003) and McCrary (2007). This dynamic effect analysis entails exploiting the timing of the adoption of advanced EMRs and including lead and lag values of adoption in our specification. Specifically, we estimate a specification that includes indicator variables for advanced EMRs for one and two years before adoption, the year of adoption reported by HIMSS, one year after adoption, and two or more years after adoption. The specification for this analysis is

$$\begin{aligned}&(\text{Log } \textit{No. of Patient Safety Events})_{it}\\&\quad=\alpha_0+\beta_{-2}D_{it+2}+\beta_{-1}D_{it+1}+\beta_0D_{it}+\beta_1D_{it-1}+\beta_{2+}D_{it-2}\\&\qquad+\lambda_3(\text{Log } \textit{Patient Days})_{it}+(\textit{Hospital Fixed Effects})\\&\qquad+(\textit{Year Fixed Effects})+\epsilon_{it},\end{aligned}\tag{2}$$

where i denotes hospital, t denotes time (year), D_{it} denotes adoption of EMR at hospital i in the year t (except that D_{it-2} includes two or more years after adoption). The lead values (β_{-2}, β_{-1}) are the anticipatory effects, and the lag values (β_1, β_2) are posttreatment or long-run effects.

The results of this analysis allow us to examine the issues of common trends and reverse causality. The aforementioned assumptions are supported if the estimates of the leads of the treatment show no effect and there is a meaningful change in the estimated effect when the treatment is introduced. Table 8 presents the result of estimating specification (2) for all events and medication events. For both these outcomes, the estimates for the leads of the treatment are small in magnitude and statistically insignificant. There is also a meaningful change in the estimates once the treatment is introduced. Figures 3 and 4 accentuate these points by plotting the estimated coefficients for the leads, at adoption, and lag values of EMR adoption.[19] In addition, these figures also suggest that the advanced EMRs lead to bigger declines in the year after adoption but the effects stablize in the second year and beyond.

Table 8. Analysis of Lead and Lags of Adoption

	(1) All b/se	(2) Med b/se
2 *Years Prior*	−0.03	−0.03
	(0.09)	(0.12)
1 *Year Prior*	0.02	−0.03
	(0.12)	(0.15)
Adoption	−0.13	−0.21
	(0.15)	(0.18)
1 *Year After*	−0.27	−0.36*
	(0.19)	(0.19)
≥2 *Years After*	−0.18	−0.43**
	(0.22)	(0.21)
Log *Patient Days*	0.21	0.14
	(0.20)	(0.20)
Hospital and year fixed effects	Yes	Yes
Variance-covariance estimator	Robust	Robust
Panel size	166	166
Observations	1,276	1,249

Note. Standard errors are calculated using cluster-robust variance–covariance estimator.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Figure 3. Impact of Advanced EMRs on All Events

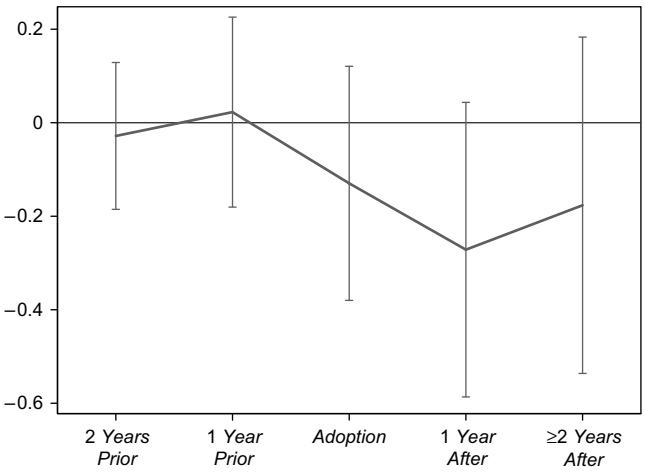
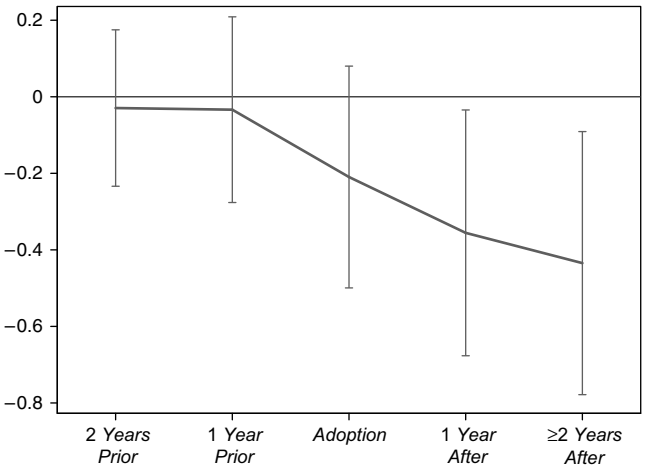


Figure 4. Impact of Advanced EMRs on Medication Events



8. Discussion and Conclusion

U.S. hospitals have invested billions of dollars in electronic medical records (EMRs) in the past decade. Although these EMR investments are expected to improve patient safety, the evidence on the impact of EMRs on patient safety has been lacking. Extant literature has not been able to provide conclusive evidence because of unreliable patient safety data, small samples, and inadequate research methods. In this paper, we analyze a panel data set of Pennsylvania hospitals from 2005 through 2014 that includes new and confidential patient safety data from the Pennsylvania Patient Safety Authority (PSA). The PSA was created by the Pennsylvania legislature in 2004. As of 2017, 27 U.S. states have enacted similar legislation that mandates patient safety reporting systems. We collated patient safety data from PSA with advanced EMR adoption and other control data from several sources. This data set allows us to use the difference-in-differences identification strategy as well as test the validity of our results using a number of robustness checks.

We find that hospitals' advanced EMR adoption leads to a 17.5% reduction in patient safety events. We further explore this overall reduction by analyzing the impact of advanced EMRs on the subcategories of errors that map to clinical processes, such as medications and procedures. Our results show that medication errors decline by 21.6%, falls decline by 17.8%, and complications decline by 16.6%. The large effects on some subcategories of errors provide insights into which hospitals are more likely to see benefits from EMR adoption. Our analysis of events by severity suggests that advanced EMRs have a significant impact, but much of the impact is concentrated around medication, fall and complication errors. Within these subcategories, the impact is large and affects events at all severity levels. Our robustness check with placebo outcomes, such as skin integrity events, does not show any impact from advanced EMRs. Additional robustness checks strengthen the validity of our findings.

In this paper, our main focus was to identify the effect of advanced EMRs on patient safety. We now consider the economic benefits of advanced EMRs with respect to patient safety. Over the 10-year study period, Pennsylvania hospitals reported approximately one-half million medication errors to the PSA. These medication errors entail a significant cost to the state's healthcare system, and a 21.6% reduction may have led to significant savings. Nationally, inpatient medication errors cost $16 billion annually, according to the nonprofit, nonpartisan Network For Excellence in Health Innovation (NEHI 2010). Extrapolating the 21.6% reduction observed in Pennsylvania to the $16 billion medication error costs in the United States, a back-of-the-envelope calculation suggests that advanced EMRs may have led to approximately $34.56 billion in national savings in medication errors over a 10-year period. In addition, a report from The Joint Commission notes that hundreds of thousands of patients fall in U.S. hospitals (Joint Commission 2015). The Joint Commission report further states that about 30%–50% of these falls result in injuries, and the average cost of a fall with injury is roughly $14,000. Combining these numbers, the estimated costs of falls in U.S. hospitals is $420 million.[20] A 16.2% reduction in these falls (with injury) would have led to an estimated national saving of roughly $680.4 million over a 10-year period.[21]

Although we expect large savings from reductions in other subcategories of errors resulting from hospitals' advanced EMR adoption, the other subcategories of errors are less amenable to rough economic benefit calculations. The Office of Management and Budget (Office of Management and Budget 2003) encourages the use of benefit–cost analysis (BCA) for health and safety issues. BCA requires monetizing of health benefits, which is difficult because 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.

Conceptually, the benefits of reducing patient safety events (resulting from medical errors) come from costs avoided in treating iatrogenic injury, costs avoided in tests or monitoring to rule out iatrogenic injury, savings from shorter length of stay, and costs avoided in duplicated or unnecessary therapies. An additional societal benefit comes from saved litigation costs as medical liability claims resulting from medical errors are a major burden on the legal system. More generally, reductions in medical errors decrease patient anxiety, alleviate patient pain, and reduce avoidable treatment caused by medical errors and complications. Finally, reductions in medical errors reduce patients' loss of confidence in hospital care.

Our paper has a few limitations. First, our data is limited to Pennsylvania whereas combining data from other states would increase the robustness of our findings. Because many other states have enacted legislation requiring patient safety reporting systems, this data will eventually be available for analysis. Second, a larger sample (formed by incorporating patient safety data from more states) would allow us to explore heterogeneous effects from advanced EMRs. Third, we do not have patient-level data because the Pennsylvania legislation requires hospitals not to disclose patient and provider identity to the PSA. While patient and provider confidentiality in PSA data fosters accurate reporting of patient safety events, lack of patient-level data makes cost estimates difficult.

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Endnotes

[1] See Section 2 for a discussion on advanced EMRs.

[2] To increase the variation, we have disaggregated basic EMR (see Section 6) rather than follow the definition of basic EMR in Dranove et al. (2014). We thank an anonymous reviewer for this suggestion.

[3] These authors further emphasize the role of CPOE in providing decision support and refrain from emphasizing "the direct Clinical Decision Support measure in the HIMSS Analytics data due to instability in the questionnaire during the survey's early years" (McCullough et al. 2016, p. 211). We also believe that the benefits of decision support largely accrue through advanced EMRs.

[4] A care provider at a major U.S. hospital remarked that he does not consider CPOE and PD to be separate entities. In his hospital, CPOE and PD are seamlessly integrated. This disappearing distinction between CPOE and PD is likely to be a secular trend as hospitals choose EMR vendors because of their integrated capabilities.

[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 November 2013).

[6] The AHA Annual Survey provides a nearly complete census of U.S. hospitals. AHA Annual Survey includes data "covering organizational structure, facility and service lines, inpatient and outpatient utilization, 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 web page; accessed November 2013).

[7] Average national hospital size is calculated from the AHA survey for 2009. Average case mix index (CMI) is calculated from the CMS data archived by NBER for 2005. Average adoption is calculated from the HIMSS data set.

[8] Also, see "Patient Safety Visual Analytics Reporting System" by Howard Newstadt (https://goo.gl/Omd3Wt): "On March 8, 2016, the Department of Health and Human Services (HHS) issued its Final Rule on the Patient Protection and Affordable Care Act's (ACA) Benefit and Payment Parameters. In the Final Rule comments, Pennsylvania's mandatory Patient Safety Reporting System was noted as one of only two examples (along with Maine) of 'robust, evidence-based, effective patient safety programs that have delivered high value and improved patient safety across their regions.' The Final Rule Response then concludes, 'We acknowledge that there could be local, State, or national patient safety reporting programs that meet or exceed the patient safety standards for . . . the QHP [Qualified Health Plan] issuer patient safety requirements.' "

[9] We thank an anonymous reviewer for suggesting that implementing EMRs likely facilitates patient safety error reporting (as implied by Miller and Tucker 2014) so any bias resulting from reporting changes would make our estimates conservative.

[10] We present this robustness check here rather than in Section 7 to conserve space.

[11] Agha (2014) also includes a state-specific time trend because her data set is national. Although we cannot include state-specific trends as our data set is from a single state, we tested with linear and quadratic county-specific time trends and found a statistically significant 18.4% decline in patient safety events. Our data set includes 60 (out of 67) Pennsylvania counties, and the addition of linear and quadratic time trends requires the estimation of 120 additional parameters.

[12] We thank an anonymous reviewer for this suggestion.

[13] Although not presented in this paper, we also reestimated specification (1) for the sample of hospitals that have had basic EMR for 10 years. We observed a higher decline for this sample than for the entire sample (as presented in Table 4). Since there is no variation in basic EMR, this analysis further suggests that the estimated benefit can be attributed to adoption of advanced EMRs.

[14] Also see Leapfrog (2016): Specific benefits of CPOE include (i) prompts that warn against the possibility of drug interaction, allergy, or overdose; (ii) accurate, current information that helps physicians keep up with new drugs as they are introduced into the market; and (iii) drug-specific information that eliminates confusion among drug names that sound alike.

[15] However, including procedure errors does not change these results substantively.

[16] We do not include the nonclinical IT as controls in the main analysis as nonclinical IT can be plausibly considered weak instrumental variables (IVs) for advanced EMRs. Including IVs as control variables can lead to bias amplification (Ding et al. 2017), so we include these variables as controls only in our robustness checks.

[17] This issue has been reported by other authors (e.g., see Atasoy et al. 2018).

[18] Readers can request detailed results from the corresponding author.

[19] Figures for other subcategories are not included to conserve space but are available from the authors.

[20] Conservatively assuming 100,000 falls per year, 30% injury rate, and \$14,000 cost per fall, we have $100{,}000 \times 0.3 \times \$14{,}000 = \$420{,}000{,}000$. Note that the \$420 million is the conservatively estimated cost of falls in hospitals only. For comparison, the year 2012 direct costs of falls in hospital, emergency department, and outpatient settings is estimated to be \$31 billion (inflated to 2015 dollars) for patients older than 65 years—our estimated cost of \$420 million is merely 1.35% of \$31 billion.

[21] The 16.2% reduction is taken from the last row of Table 7, column (6).

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