Reassessing the Impact of Health IT: Hidden Costs and Consequences of Vendor Heterogeneity

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August 18, 2021

Abstract

We examine how vendor heterogeneity affects electronic medical records (EMR) performance in U.S. hospitals. Although the government has invested billions to encourage the adoption of health information technology, there is little evidence showing that it is producing the expected effects. Based on a national sample of hospitals and using a fixed effects model, we find that the impact of EMR adoption on hospital costs and adverse drug events among Medicare patients varies substantially by vendor. Not all certified EMRs lead to cost savings or improvements in quality of care. Few EMR vendors deliver both cost savings and improved patient quality. Instead, most vendors who offer improvements in patient quality have increased costs, reflecting a pattern of substitution. Our results suggest that there are trade offs and consequences for hospitals of adopting different EMR vendors and raise questions about whether government certification standards for EMR systems are sufficient. The variability in EMR performance among vendors shown in our study suggests that there is a hidden cost to the government's standards.

JEL Codes: H51, I11, I13, I18, O33
Keywords: Healthcare costs, health IT, hospitals, vendor heterogeneity

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1 Introduction

The diffusion of information technology in the health sector is expected to reduce costs, improve productivity, and enhance the quality of patient health outcomes. For these reasons, accelerating the pace of health IT (HIT) diffusion has been an important goal of policymakers. To further this goal, politicians passed the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, which provided generous subsidies to eligible hospitals and physicians to adopt certified Electronic Medical Records (EMRs). Although billions of dollars have been spent on subsidies and the use of EMRs in hospitals has become widespread, prior research has found little systematic econometric evidence that EMRs are reducing costs or producing the anticipated effects. These studies have assumed products made by different vendors are homogeneous, but the assumption may not be warranted in the competitive and sophisticated health IT industry. EMR systems made by different vendors may vary and perform differently in hospitals.

Examining the impact of EMRs on hospital costs or clinical outcomes is a particularly interesting issue to study. EMRs allow hospitals to manage and process health care information more efficiently, which in theory may lower health care costs and improve clinical outcomes. Prior research predicted that widespread use of EMRs in hospitals would produce substantial benefits (Hillestad et al., 2005). Case studies found benefits of HIT adoption for select institutions (Chaudhry et al., 2006; Goldzweig et al., 2009; Buntin et al., 2011). However, studies involving a national sample of hospitals have found little evidence that EMRs reduce costs and found mixed evidence that EMRs improve clinical outcomes. The limited and mixed evidence of benefits presents a puzzle for policymakers, who have invested billions to encourage EMR adoption under the HITECH Act, and raises questions about why EMRs have not yet lived up to expectations. Accounting for differences in the EMR systems made by different vendors may help resolve this puzzle.

EMRs are complex software systems that may vary in several ways. There may be differences in the kinds of information that can be captured and how that information is managed, stored, and presented. Physicians may input or access information differently in the systems of different vendors. Systems that are easier to use may improve care coordination and lead to efficiencies, while systems that are difficult or overly complicated to use may lead to inefficiency. Although

the government has federal certification criteria for EMR vendors, those criteria represent more of a baseline or lower bar. Vendors have discretion to develop and differentiate their EMR systems. Studies have noted variability in certified EMR systems (Sittig et al., 2015; McCoy et al., 2015; Ratwani et al., 2015), but there has been little study of how such variability impacts hospital costs and patient outcomes.

This paper examines how the adoption of different EMR vendors affects EMR performance in hospitals. Our analysis exploits the variation among adopting and non-adopting hospitals as well as variation among the EMR vendors selected to explore these effects. We focus on the Medicare population and examine how EMR adoption affects average hospital costs per stay, average hospital expenses, case mix index, adverse drug event rates, and condition specific 30-day mortality rates using data from Medicare Hospital Cost Reports and inpatient claims data. We also examine how EMR adoption affects the number of inpatient stays and procedures to gauge effects of adoption on the volume of hospital services. We identify a hospital's decision to adopt an EMR and its EMR vendor using 2006 to 2010 data from the Health Information Management System Society (HIMSS) Analytics database. We examine how the adoption of an EMR affected the outcome relative to what that hospital would have experienced if it hadn't adopted the EMR. We test for two possible sources of endogeneity associated with EMR adoption: (1) the timing of adoption could be correlated with the unobserved changes at the hospital level that may also affect the outcomes; (2) conditional on adoption, the specific vendor selected could also be related to changes in hospital outcomes. Our tests show that there is no evidence of differential pre trends or endogeniety in either case. Then we use a fixed effects model to compare the impact of EMR adoption on hospital performance outcomes with and without vendor heterogeneity. Our analysis also controls for a rich set of hospital characteristics extracted from the American Hospital Annual (AHA) survey.

Results show the differences among EMR vendors matter for assessing these effects. Without vendor heterogeneity, results show no cost savings arising from EMR adoption, which is consistent with most of the prior studies. With vendor heterogeneity, results show reductions in the cost of providing inpatient hospital care from the adoption of two vendors (ranging from 3.6% to 4.9%), increases in inpatient costs from the adoption of three vendors (ranging from 3.5% to 16.7%), and no significant effects from the adoption of other vendors. We observe similar variability for the

other financial measures, average hospital expenses and the case-mix index. For patient outcomes, results show that EMR adoption reduces the rate of adverse drug events (ADEs) between 0.67% and 1.7% for the users of four vendors, increases the rate for the users of one vendor by 0.3%, and has no significant effects for the adopters of other vendors. There is little evidence that EMR adoption (of any vendor) leads to reductions in condition-specific mortality rates.

Our analyses show that few vendors deliver both cost savings and improved patient quality at the same time for adopting hospitals. Instead, most vendors who achieve improvements in patient quality have increased costs, more of a pattern of substitution. In addition, only some vendors who deliver improved patient quality do so with higher inpatient stays. For other vendors, improvements in patient quality come with fewer inpatient stays. These results show that there are trade offs to hospitals of adopting different EMR vendors.

Overall, our study shows that a failure to account for the differences among vendors masks important variability in assessing the effects of EMRs on hospital performance and patient outcomes. It also helps explain why past studies found little to no evidence of cost savings or quality improvement arising from EMR adoption. If all the in-sample hospitals adopt the vendors that lower hospitalization costs, a back-of-the-envelope estimation suggests annual savings would range from $8.35 billion to $11.4 billion. The annual savings could range between $17.5 billion and $23.9 billion when extrapolating to the national sample.

Our study builds upon prior research that has assessed the impact of HIT in two ways. First, we show the importance of accounting for EMR vendor heterogeneity in assessing EMR effectiveness. Second, we provide evidence that the benefits of EMR adoption fall on the users of particular vendors. Prior studies that haven't accounted for vender heterogeneity found little evidence of cost savings following EMR adoption (Agha, 2014; Dranove et al., 2014) and mixed evidence about the impact of HIT adoption on patient outcomes (Agha, 2014; McCullough et al., 2016; Haque, 2014; Miller and Tucker, 2011; Freedman et al., 2018). Evidence of variability in the performance of EMRs from different vendors have important implications for hospitals who must choose among those EMR vendors, and patients who must choose among hospitals.

Our study has important implications for the government's incentive program for HIT adoption. Although health care providers may receive subsidies for a variety of "certified" vendors, as

long as they meet the conditions of "meaningful use," our results show that not all certified EMRs produce the anticipated benefits of cost savings or improved patient outcomes. Our results raise new questions about whether the government's certification standards for EMR systems are sufficient, similar to the policy insight by Holmgren et al. (2017). Differences among the products of HIT vendors offer more choice and flexibility to hospitals; however, a failure of all certified products to deliver the expected benefits means that the regulations come with a hidden cost. Hospitals who adopt these vendors will not learn about these costs until after they make substantial investments in HIT. In light of this, policymakers may want to inform providers (ex ante) about the differences among EMRS made by different vendors. They could also strengthen the requirements for HITECH program participation by ensuring that certified EMRs are delivering cost savings and improved patient care.

The paper is structured as follows. Section 2 provides the institutional background on EMRs and the HITECH Act. Section 3 discusses data sources and section 4 presents the summary statistics. Section 5 describes the methods and section 6 presents our results. Section 7 offers some concluding remarks.

2 Background

2.1 EMRs and the features of the industry

Health IT is regarded as a promising tool to improve overall quality and efficiency of the health care delivery system. EMRs provide the foundation for a hospital's health information technology system. EMRs allow health care providers to store, access, retrieve, and exchange patient information using computers instead of more traditional paper records. The adoption of EMR systems could "cause substantive changes in processes, work routines, and established patterns of interaction among organizational actors" (Brynjolfsson and Hitt, 2000; Angst et al., 2010).

As noted by Dranove et al. (2014) an EMR system is a "catch all expression used to characterize a wide range of information technologies" designed to accomplish the functions described above. These technologies include, but are not limited to, the following applications: clinical data

repository (CDR), clinical decision support capabilities (CDS), order entry (OE), computerized physician/provider order entry (CPOE), and physician documentation (PD). Dranove et al. (2014) note that "there is no single technology associated with EMRs, and different EMR technologies may perform overlapping tasks." CDR is a centralized database that collects, stores, accesses, and reports health information, including demographics, lab results, radiology images, admissions, transfers, and diagnoses. It provides a full picture of the care received by a patient. CDS combines clinical information and individual data to assist providers in decision-making tasks, such as determining the diagnosis or setting treatment plans. OE is an automated process of entering orders for ancillary services such as lab work or radiology into an electronic billing system. CPOE allows physicians to enter prescribing or other service orders electronically and it offers more sophisticated drug safety features such as checks for drug allergies or drug interactions. With these features, CPOE may potentially reduce adverse drug events and other errors arising from poor coordination among different providers. PD offers physicians structured templates for creating clinical documentation of a patient's condition and course of treatment.[1] Based on the difficulty in implementation and operation, the first three applications (CDR, CDS, and OE) represent more basic components, while the remaining two (CPOE and PD) are advanced applications (Dranove et al., 2014).

The EMR products made by different vendors may vary in important ways, such as the way that test results and other information are displayed (Sittig et al., 2015), aspects of design that influence the way physicians interact with the system (Ratwani et al., 2015), decision support capabilities (McCoy et al., 2015), data storage and organization, training, customer support, and system maintenance. Each vendor may have its own advantages and some systems may be easier to use than others. The variability in EMR systems and users' experiences with those systems may impact physician practice, physician interactions, and change the delivery of care, which will further vary the levels of performance.

EMRs have the potential to increase efficiency and health care quality via a number of mechanisms. The technology collects all patient information in one place, including medical history,

[1]These templates may help physicians document a patient's daily progress, operative notes, consult notes, emergency department (ED) visits, discharge summaries and other relevant information during a hospital admission. PD also generates diagnostic codes from this information that may be useful to other providers or used for reimbursement.

diagnoses, medications, treatment plans, immunization dates, allergies, radiology images, and lab test results. Physicians are able to access all relevant information at the point of making decisions, which is essential for safe and effective care. Readily available information may avoid physicians ordering excessive lab work and imaging. Information gathered by EMRs can aid in diagnosis, reduce errors, and improve patient outcomes. For instance, the system with a patient's historical records will automatically check for problems whenever a new medication is prescribed and alert clinicians to potential adverse events. Combining individual records with medical literature, EMRs enable evidence-based decisions and provide reliable guidance. By automating paper-driven and labor-intensive tasks, EMRs streamline clinician work flow, which helps decrease operational costs such as on transcription services, chart refill, and storage.

However, EMRs also create new burdens on physicians that may lead to inefficiencies (Gawande, 2018). For instance, new demands on physicians for data entry using computers takes extra time and may lead physicians to see fewer patients. Even with some cost savings, EMRs might translate into fewer patients and lower patient revenue, which adversely affects a hospital's bottom line. Another concern is that EMRs may make it easier to manipulate medical records to increase reimbursement amounts, a practice known as upcoding.[2] Given the range of possible effects, it becomes even more important to empirically study the impact of vendor-specific EMRs in hospitals.

2.2 HITECH Act

The application information technology in the U.S. health care sector has lagged behind other developed countries (Jha et al., 2008). Only in the last decade have health care providers started to pick up this technology, mostly spurred by the federal incentive program.

President George W. Bush first outlined such a program in 2004 in which most Americans would have electronic health records within 10 years. The president's FY2005 budget proposal included funding for $100 million for demonstrative projects to test the effectiveness of health IT. The Office of the National Coordinator for Health Information Technology (ONC) and the American Health Information Community (AHIC) were established after this proposal and organized a

[2]Some EMR vendors have marketed their systems to hospitals as a way to increase billable charges and patient revenue.

number of meetings with the public and private sectors in 2006-2007 to discuss the prototypes of the Nationwide Health Information Network (NHIN) and strategies to support health IT. These actions and meetings may have increased industry expectations of future subsidies for EMR adoption prior to the actual passage of the Act.

In 2009, the HITECH Act was passed as part of the American Recovery and Reinvestment Act to promote the adoption of health information technology. The HITECH Act proposed that health care providers would be offered financial incentives for demonstrating meaningful use (MU) of health IT—using certified EMR technology in a meaningful manner—to help ensure that the technology would enhance the overall organizational performance in the health care sector. Hospitals who had adopted health IT prior to the policy were also eligible for the incentive payments as long as their EMR system could meet the MU requirements. The Office of the National Coordinator for Health IT developed a certification process for EMRs to help ensure that certified vendors' products met the "technical" meaningful use requirements. However, the certification process takes place in a controlled environment that may not perfectly reflect the flow of medical information in real-word clinical settings (Holmgren et al., 2017; AAFP, 2015). While there are a variety of certified EMR products—245 certified inpatient EMRs and another 616 certified components (Tripathi, 2012)—in the certified product list, one may wonder whether all of them are equally capable, especially given variability in the system design and operation.

The roll out of the program and the MU requirements were scheduled to occur in three stages. Eligible Professionals (EP) and Eligible Hospitals (EH) would be awarded incentive payments for demonstrating the completion of MU criteria in each stage. The first stage, launched in 2011, introduced a minimum set of core objectives and MU criteria/requirements that an EMR system had to meet to be eligible for subsidies. These initial requirements included features such as the electronic entry of clinical information, patient demographics, diagnoses, allergies, etc. Stage two, launched in 2014, added more advanced processes to the meaningful use criteria, such as more rigorous health information exchange, increased requirements for e-prescribing and incorporating lab results, more patient controlled data, and electronic transmission of patient summaries across multiple settings. Stage three, effectively mandated in 2018, attempts to reduce the complexity of the program established in the previous stages and, instead, only specifies eight overall objec-

tives. The Centers for Medicare and Medicaid Services (CMS) have adjusted and amended the requirements and deadlines over time to accommodate eligible providers. The evolution of these regulations has advanced the development of the health IT industry.

EMR vendors have to meet the certification criteria specified by the CMS and ONC. The standards and criteria have been published as proposed rules and updated over time according to the stage of the program. Thus, EMR vendors have an opportunity to scrutinize the proposed requirements, comment on them, and adjust their products accordingly. CMS has even removed several core requirements in the most updated MU criteria, as those have been widely adopted by the industry. While the MU requirements are designed to ensure that each vendor's system meets a common set of objectives, the incentive program, per se, has led to more heterogeneity and advanced innovation in the industry.

3 Data

To examine the effects of vendor heterogeneity on EMR performance in U.S. hospitals in 2006-2010, we use data from the following sources: Hospital Cost Reports, the Medicare Provider Analysis and Review (MedPAR) File, the Healthcare Information and Management Systems Society (HIMSS) Analytics Database, and the American Hospital Association (AHA) Annual Survey.

We construct two financial outcome measures—average hospital costs per stay and average expenses per stay—using Hospital Cost Reports. CMS requires Medicare-certified institutional providers to submit an annual cost report that includes provider-specific characteristics, utilization data, cost and charges by category (in total and for Medicare), and various financial statement data.[3] We calculate the average hospital costs by summing the costs of three types of services: routine, special care, and ancillary (Coomer et al., 2017) and dividing by the total number of inpatient stays.[4] We believe this measure covers a wide range of inpatient hospital services that could be impacted by the application of health IT. We calculate average hospital expenses by

[3] https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports

[4] According to Coomer et al. (2017), routine services refer to those typically provided to all patients. Special care represents specialized services including intensive care and coronary care. Ancillary services are rendered outside of routine and special care, such as radiology, laboratory, physical therapy, and supplies.

taking the sum of direct costs and salaries across all departments, such as the expenses on plant operations, administrative salaries, utilities, and so on and then dividing by the total number of inpatient stays. EMR adoption may also affect a hospital's financial performance in aspects other than the provision of care, such as operation, staffing, capital depreciation, and so on. Our unit of analysis is at the hospital/year level, so each outcome variable is constructed as an annual average across all in-sample patients admitted to that hospital in a given year.

We use MedPAR to develop a third financial outcome—the case mix index (CMI)—and patient outcome variables. MedPAR contains information on inpatient hospital stays for all Medicare beneficiaries. Each observation in these data corresponds to an inpatient stay and contains information on the hospital, the beneficiary's home zip code, age, gender, dates of service, reimbursement amount, dates of admission and discharge, Diagnostic Related Group (DRG), and principal and secondary diagnoses. From this data, we construct the CMI, equal to the total DRG weights across all inpatient stays divided by the number of inpatient stays. It is an average DRG relative weight for that hospital and represents the costliness of its Medicare patient mix. We study this outcome in order to understand how health IT adoption affects a hospital's resource consumption on its Medicare patients.

We also use the MedPAR data to construct patient outcomes, namely adverse drug event (ADE) rates and condition specific 30-day mortality rates. These measures are used by the government to assess hospital performance and also commonly studied in the literature. Following Agha (2014), the ADE rates, defined as the number of inpatient stays with ADEs divided by the total number of inpatient stays in a hospital, are constructed on the basis of provider-reported ICD-9 and ICD-10 codes. We draw upon Hougland et al. (2008) and Poudel et al. (2017) for the codes representing adverse drug events. They include failures in dosage, accidental poisoning by drugs, or complications caused by the use of a medication. We also examine differences in ADE rates by patient complexity. Following the literature, we categorize a complex patient as one who has been admitted in the previous 12 months.[5] The rationale is that patients deemed complex may be more likely to experience an adverse drug event, while patients with less complexity (who haven't been

[5]We also tried other measures to control for complexity, such as the number of secondary diagnoses and Charlson Comorbidity Index. These results are robust and available upon request.

admitted in the last 12 months) may have a lower rate of adverse drug events.

Our analysis on mortality rates focuses on three specific conditions: pneumonia, congestive heart failure (CHF), and acute myocardial infarction (AMI). These conditions are common among the elderly population and associated with substantial mortality and comorbidity. As a result, they are typically studied in the literature and the quality of treating them is part of the core measures monitored by CMS (Haque, 2014; McCullough et al., 2016). We identify a patient with a particular disease if the patient's primary diagnosis includes a defined ICD-9 code for this disease.[6] We calculate each 30-day mortality rate based on the number of patients who suffer from each condition. The definition of 30-day mortality follows the guideline from the CMS.[7]

Our hospital information technology adoption data come from the HIMSS Analytics Database. This is a national database, which covers the demographic and automation information of the majority of U.S. hospitals and includes purchasing plan details for over 90 software applications and technologies. The data is collected from an annual survey that records a hospital's IT choices and capacities over time. This dataset contains information about a hospital's EMR adoption status, year of adoption, component installed, and identity of the vendor reported in each year from 2006 to 2010.

Prior studies defined EMR capabilities by either enterprise EMR[8] or CPOE (Lee et al., 2013; McCullough et al., 2016; Ganju et al., 2015). We define a hospital to have adopted EMRs if the component CPOE has been installed in the hospital in a given year during our period of study.[9] We focus on CPOE because of its potential to reduce medical or drug-related errors and improve patient quality of care. As a robustness test, we also examine an alternative definition of EMR adoption as a hospital that has installed either of the two advanced components, CPOE or PD, during our period of study. We supplement our HIT data with key hospital characteristics obtained from the American Hospital Association (AHA) Annual Survey. The AHA data includes a rich set of hospital-specific features such as hospital beds, admissions, births, inpatient days, system

[6] Appendix Table A1 reports the ICD-9 codes corresponding to each of these conditions.

[7] https://www.medicare.gov/hospitalcompare/Data/30-day-measures.html

[8] The record for enterprise EMRs discontinued in the data beginning in 2008, so our definition of adoption does not depend on it.

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

affiliation, organization structure, ownership status, and other characteristics. We match data from the three sources above using a hospital's Medicare provider number.[10]

We start with approximately 4,900 hospitals per year in the HIMSS analytic database, and the number drops to about 4,500 after merging with AHA annual survey. With five-years of data, there are 22,450 observations in total. We then remove hospitals who were dealing with multiple vendors in the same year during the sample period, and the total number drops to 19,011.[11] We only keep the first-time CPOE adopters and hospitals that had not adopted CPOE by the end of the sample period, which leaves us with 16,262 observations. We merge the health IT data with the hospital cost reports, with approximately 84% of hospitals matched for hospital costs and over 99% for hospital expenses.[12] In our sub-analysis which adjusts for patient complexity, the number of observations varies because some hospitals drop out of the sample if they do not have any patients who were previously admitted in the last twelve months. The number of hospitals in the analysis for condition-specific mortality rates also varies, depending on the disease considered.[13]

4 Summary Statistics

Figure 1 shows an increasing trend in initial EMR adoption during the sample period. Hospitals who adopted EMRs (defined as CPOE) increased from 3.85% in 2006 to 26.2% in 2010.[14] The increase in adoption observed during our sample period correlates with an increase in activity to promote HIT during the Bush administration.[15] This activity may have fueled hospital expectations of a government incentive program for EMRs even prior to the actual passage of the HITECH

[10]In cases where the Medicare provider number was missing, we merge the datasets using the hospital's name and geographic information.

[11]Multiple vendors make it difficult to examine the effect of a single vendor on performance.

[12]We drop a hospital (with four observations) in the all-patient ADE rate due to an unusual increase in the number of adverse drug events in this hospital during the sample period.

[13]We further lose observations when constructing the index admission for the 30-day mortality rate. The index admission is the starting point for analyzing repeat hospital visits. (Healthcare Cost and Utilization Project, 2012). We only include patients whose index admission occurs in our sample period.

[14]The small fraction of adopters in 2006 suggests that relatively few hospitals initially adopted CPOE, an advanced EMR component.

[15]The Office of the National Coordinator for Health Information Technology (ONC) and the American Health Information Community organized a number of public-private sector meetings in 2006-2007 to discuss the prototypes of the Nationwide Health Information Network (NHIN) and strategies to support health IT.

Act.[16]

Table 1 presents the summary statistics for the outcome variables. The average cost per inpatient stay increases from $12,832 in 2006 to $16,011 in 2010. The average expense per inpatient stay also increases from $18,564 in 2006 to $23,820 in 2010. The case mix index, which is an indicator for the costliness of a hospital's Medicare patient mix, increases from 1.19 in 2006 to 1.24 in 2010. The average adverse drug event rate increases from 5.5% in 2006 to 8.7% in 2009, but then falls to 6.44% in 2010. The ADE rate is higher for complex patients than for less complex patients, but follows a similar trend. The average 30-day mortality rates for each of our three conditions are declining over the sample period. The 30-day mortality rate for Acute Myocardial Infarction (AMI) declines from 19.8% in 2006 to 16.5% in 2010, while the mortality rates for Pneumonia and Chronic Heart Failure (CHF) fall from 12.7% and 14% in 2006 to 10.9% and 12.8% in 2010, respectively. Both variables measuring hospital workload also increased over time.

Table 2 reports summary statistics for the hospital characteristics in our analyses broken down by EMR adoption status. Non adopting hospitals are those that never adopt CPOE before or during our sample period. Adopters include all hospitals who initially adopt CPOE during the sample period and for the purposes of this table, we include only pre adoption observations. The summary statistics show that initial EMR adopters are more likely to be bigger hospitals with more beds, more admissions, more births, and more inpatient days. Adopters are also more likely to be non profit and teaching hospitals and less likely to be for profit and critical access hospitals. To address these level differences between adopters and non adopters, we include hospital fixed effects in our regressions as well as time varying hospital characteristics. We will also test for the possibility of differential pre trends among our adopters and non adopters to support the validity of our estimation strategy.

5 Empirical Strategy

[16]Even if hospitals contracted with an EMR vendor after the HITECH act was passed, those systems would be less likely to be live and operational by 2010 given the lag time between live and operational and contract stage.

5.1 Initial EMR adoption: No vendor heterogeneity

We first estimate the effect of EMR adoption on hospital performance using a difference in differences model that relies on variation in the timing of adoption to identify the effects. This model compares the costs and quality of care outcomes for hospitals who initially adopt EMRs (in 2006 to 2010) and hospitals without EMRs (never or non adopters). We focus on a hospital's initial adoption of EMRs to better identify the effect of the health information technology on hospital performance.[17] This case provides a benchmark for assessing EMR performance.

We estimate the following regression

$$Y_{it} = \beta \text{adopt}_{it} + \alpha_i + \theta_s + \phi_t + \gamma_{st} + \delta X_{it} + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the outcome variable for hospital i in year t. The variable $\text{adopt}_{it} = 1$ if hospital i adopted CPOE in year t and afterwards.[18] We include hospital fixed effects α_i to control for time-invariant factors at the hospital level that may also influence the outcomes. We include state fixed effects, year fixed effects, and state-year fixed effects γ_{st} to allow for unrestricted, differential trends by state to capture time-varying unobservables in patient population, medical practice patterns, or the implementation of health care policy at the state level. X_{it} is a vector of characteristics of hospital i at time t. These characteristics include staffed beds, total admissions, total births, percentage of Medicare discharges, percentage of Medicaid discharges, an indicator for whether the hospital is part of a hospital system, profit status, integration level with physicians (whether a hospital is an independent physician association hospital or whether it is organized as a management service organization), whether it is in a foundation model, whether it is in an equity model, whether it is a critical access hospital, and whether it is a teaching hospital. We interact the value of most characteristics in the base year 2006 with a linear time trend to allow for time-variation at the hospital level.[19]

[17] We exclude hospitals who adopted EMRs prior to the sample period because they lack a pre period and those who switched EMRs during the sample period to avoid any overlap in the pre and post adoption periods.

[18] We will conduct an alternative estimation that defines adoption based on the installation of either CPOE or PD and report the results from that estimation in the appendix for comparison.

[19] For instance, for-profit hospitals may demonstrate a different pattern in financial performance compared with not-for-profit hospitals.

We estimate equation (1) on the panel dataset using our fixed effects model. The coefficient of interest is β, which measures the impact of EMR adoption on an outcome measure. We are specifically interested in the extent to which EMRs lower costs or improve patient outcomes. Each unit of observation is the average across all in-sample patients admitted to that hospital in a particular year. Accordingly, we weight observations by the number of inpatient stays at the hospital level. We cluster our standard errors at the hospital level.

5.2 Test of a common trend in hospital outcomes among EMR adopters and non adopters

An important assumption of our estimation strategy is that there is a common trend in our hospital outcomes among adopters and non adopters prior to EMR adoption. If there are time varying factors that influence both EMR adoption at time t and our hospital outcomes, then we may not observe a common pre trend. For instance, unobserved local market or hospital characteristics may impact both a hospital's decision to adopt an EMR and affect its outcomes. To test for a common trend, we estimate equation (1) but replace the key adoption term with a indicator variable for our treatment group (EMR adopter) that is now interacted with a set of dummy variables for each year t prior to and after the adoption decision. The coefficients for these interaction terms reveal the extent to which the trend for the treatment group differs relative to the control prior to and after EMR adoption (Autor, 2003).

Figures 2, 3, and 4 show that coefficients for the treatment group trend prior to EMR adoption are not significantly different than zero for our financial measures, ADE rates, and mortality measures, respectively. We tested the joint significance of the pre period coefficients (by outcome) and could not reject that they were all jointly zero, which suggests that we can not reject the premise of a common pre trend among treatment and control groups. These p values are reported in the first column of Table 3.

5.3 Vendor-specific effects

Our second specification allows for vendor heterogeneity and examines whether the EMRs from different vendors have differential effects on hospital performance. Building upon (1) we estimate:

$$Y_{it} = \sum_{k=1}^{K} \beta_k \text{vendor}_{it}^k + \alpha_i + \theta_s + \phi_t + \gamma_{st} + \delta X_{it} + \varepsilon_{it} \tag{2}$$

Let k represent a particular vendor from the set of active vendors in the market, $\{1, 2, ..., K\}$. We assume $\text{vendor}_{it}^k = 1$ if vendor k was adopted in hospital i at time t and afterwards. We include 12 major vendors of inpatient EMR systems and group those remaining into a class called "others".[20] These vendor-specific dummy variables will better determine the impact of different vendors' EMR systems on hospital performance by controlling for potential variation among EMR systems, such as the way that test results and other information are displayed, the way that physicians interact with the system, and differences in training programs, customer support, and system maintenance (software upgrades). As in (1) we control for hospital fixed effects α_i, state fixed effects, year fixed effects, state-year fixed effects γ_{st}, and a rich set of hospital characteristics X_{it}.

5.4 Test of a common trend in hospital outcomes among adopters of different EMR vendors

Testing for a common pre trend in hospital outcomes among adopters and non adopters becomes more complicated with vendor heterogeneity. There are now multiple dimensions of differential trends to consider. First, there may be unobserved factors that influence the timing of EMR adoption and our hospital outcomes. Second, conditional on adoption there may be unobserved factors that influence the choice of a particular EMR vendor and hospital outcomes. Unobserved local market characteristics or hospital characteristics may appeal to certain vendors, and those characteristics may also influence hospital performance. Both could lead to differential pre trends and pose a source of bias to OLS estimates. We examine these issues separately for greater clarity and transparency and use a two step process to test for common pre trends. First, we identify a base-

[20] The sales of these twelve vendors represent 92% of the market share in the EMR market in 2006.

line vendor defined as the most popular EMR vendor, Meditech. We examine whether there is a common pre trend in hospital outcomes among Meditech EMR adopters and non adopters (of any vendor) prior to adoption. Second, we examine if the pre trends in outcomes for the hospitals who adopt other vendors are significantly different from the hospitals who adopt the baseline vendor, Meditech. This allows us to examine if there is a common pre trend among our baseline vendor and each alternative vendor. The intuition behind these tests reflects two possible endogeneity problems. The first is the decision to adopt an EMR and the second is the decision to select a particular vendor. We estimate a regression similar to (2) that includes a term for our treatment group (adopter of vendor k) that is now interacted with a set of dummy variables for each year t prior to and after the adoption decision. Then we can examine the coefficients of these interaction terms for the years before adoption for each vendor to determine (i) if the pre trend differs among our baseline vendor relative to the control group (non adopters of any EMR) and (ii) if the pre trend for each alternative vendor differs from our baseline vendor, Meditech. In the first case, we test for whether the coefficients of the interaction terms for the adopters of our baseline vendor, Meditech, are jointly zero for the years prior to adoption. In the second case, we test for whether the coefficients of the interaction terms for each alternative vendor are significantly different than the coefficients for our baseline vendor, Meditech, in the pre period.

We summarize the results from these tests in Table 3. In column 2, we first indicate whether Meditech has a common pre trend relative to the control group for each outcome. In column 3, we report the number of vendors that are not significantly different from Meditech in the pre period for each outcome. The results in column 2 show that we can not reject the premise of a common pre trend among our baseline vendor, Meditech, and the control group (non adopters) for all outcome variables. This suggests that possible endogeneity due to the timing of EMR adoption does not pose a threat to our research design. Results in column 3 show that the pre trends for most EMR vendors are not significantly different from our baseline vendor, Meditech, for most outcome variables. While this provides strong evidence that possible endogeneity from the choice of vendor does not threaten our research design for most outcomes, the results cannot perfectly preclude the endogeneity in vendor choice, conditional on adoption.[21] In the case of the AMI mortality rate,

[21] As an addition check, we conduct our analysis without the two vendors whose coefficients are significantly

coefficients for less than half of the vendors (5/12) are not significantly different from Meditech. For this outcome in particular, possible endogeneity due to the choice of vendor limits our ability to draw a causal inference about the effects of a hospital's vendor choice on the AMI mortality rate.

6 Results

6.1 No vendor heterogeneity

The regression results without vendor heterogeneity are presented in in Table 4 as a benchmark. For simplicity we report only the coefficient of interest β's, which represents the marginal effects of EMR adoption on each outcome measure.

Results show that on average EMR adoption has no significant impact on hospital costs (average hospital costs, average expenses, CMI) and patient quality measures (ADE rates, and condition specific mortality rates). Agha (2014) also found no evidence that EMR adoption reduced medical expenditures and no significant effect of adoption on 30-day mortality. We observe that EMR adoption is not significantly associated with any change in the rate of adverse drug events on average (with and without adjustment for patient complexity), a result that differs from Agha (2014) who finds a positive coefficient and Freedman et al. (2018) who observes a negative effect for less complex patients.[22] Without vendor heterogeneity, the results suggest that government efforts to incentivize EMR adoption yield no cost savings or quality of care benefits for patients. Next, we allow for vendor heterogeneity and examine whether the EMR systems made by different vendors produce heterogeneous effects on hospital performance.

different from Meditech (in the average costs and ADE expressions) and find that the results are not affected: same sign and same significance level for the coefficients. We also conduct another analysis without the three vendors whose coefficients are significantly different from Meditech (in the average expenses, CMI, ADE complex, ADE less complex, and PN, CHF mortality expressions) and find that the results are similar for the average expenses, CMI, ADE outcomes, an PN mortality rate: same sign and same significance level for the coefficients, and mostly similar for the CHF mortality rate.

[22] Agha (2014) examined an earlier time period but did focus on Medicare patients. Freedman et al. (2018) focused on a non Medicare population.

6.2 Vendor-specific effects

Table 5 presents the results (with vendor heterogeneity) for the financial outcomes; average hospital costs per stay in column one; average hospital expenses in column two; and case mix index in column three. Each row shows β_k for a particular vendor, which represents the marginal effects of EMR adoption of vendor k on each outcome measure. The bottom of each column reports the p values associated with the tests for joint insignificance and joint equality of the vendor-specific coefficients.

Table 5 shows that the impact of EMR adoption on average hospital costs per inpatient stay varies substantially by vendor. With vendor heterogeneity, we see negative coefficients for the adopters of two EMR vendors, which suggests costs savings (ranging from 3.6% to 4.9%) in adopting hospitals. However, not all vendors produce such cost savings. We see positive coefficients for the adopters of three other EMRs vendors, which indicates cost increases (ranging from 3.5% to 16.7%) for adopting hospitals. For the remaining vendors, we see no significant effects of EMR adoption on average hospital costs per stay. We also observe variability for the other financial measures, average hospital expenses per stay and the Medicare case-mix index (CMI). With vendor heterogeneity, results show reductions in the average hospital expenses (ranging from 2.6% to 6.8%) from the adoption of two vendors, increases in average hospital expenses (ranging from 3.5% to 5.3%) from the adoption of two other vendors, and no significant effects on hospital expenses from the adoption of remaining vendors. Results also show that the adoption of different EMR vendors can affect the CMI or the costliness of the Medicare patient mix in hospitals in different ways. We see reductions in the CMI (ranging from 2.5% to 4.7%) from the adoption of two vendors, which suggests a decline in the average DRG weight of Medicare patients treated or a decline in the costliness of the Medicare patient mix in hospitals.[23] However, we also see an increase in the CMI (1.7%) from the adoption of one other vendor, which suggests an increase in the average DRG weight of the Medicare patients treated or an increase in the costliness of the Medicare patient mix in hospitals.[24] Hospitals who adopted remaining vendors saw no significant effects on

[23] Such a reduction would occur if EMRs allow hospitals to treat more patients who are less costly to treat on average.

[24] An increase in the CMI is consistent with the argument that the adoption of more advanced technology either attracts or allows for the treatment of patients who are more costly on average.

the CMI. The p-values at the bottom of the all columns indicate that we can reject that the vendor effects are jointly zero and that the vendor effects are jointly equal at conventional significance levels. This evidence suggests that the impact of EMRs on average hospital costs per inpatient stay, average hospital expenses, and the CMI are not the same among the vendors and only some vendors deliver on the promise of cost savings, while others result in either increased costs or no change in hospital costs. The differences between EMR vendors matter and have different cost implications for adopting hospitals.

Table 6 shows the impact of EMR adoption on ADE rates with and without adjustment for complexity. The first column presents vendor effects for all patients without adjustment for complexity; the second column presents the vendor effects for complex patients; and the third column reports the vendor effects for patients not deemed complex. Without adjustment for complexity, EMR adoption reduces the rate of adverse drug events (ADEs) for the adopters of four vendors. The magnitude of the reduction ranges from .67 to 1.7 percentage points, which is 10.2% to 25.9% of the mean ADE rate.[25] This represents an improvement in patient quality of care for the hospitals who adopted these vendors. We also see an increase in the ADE rate for the users of one vendor by 0.3 percentage points, and no significant effects for the adopters of remaining vendors. Results in column 2 show reduced ADE rates for complex patients arising from the EMR adoption from three of these vendors, which range from .6 to 1.8 percentage points (8.7% to 24.5% of the mean ADE rate).[26] An increase in the ADE rate observed for the adopters of one vendor is also seen for complex patients. Among less complex patients, the EMRs from five vendors lead to reductions in ADE rates that range from .7 to 2.3 percentage points (11.2% to 37.4% of the mean ADE rate).[27] Two vendors are significantly associated with an increase in the ADE rate, with no significant effects of EMR adoption observed for remaining vendors. The p values at the bottom of each column indicate that the vendor effects are jointly significant, and we are able to reject their joint equality. Vendor effects continue to matter for explaining changes in ADE rates.

Table 7 reports the impact of EMR adoption by vendor on 30-day morality rates for Pneumonia, Chronic Heart Failure (CHF), and AMI, in the first, second, and third columns respectively. There

[25] 10.2% = 0.67 / 6.57 and 25.9% = 1.7 / 6.57, where 6.57 is the average ADE rate across the five years.
[26] 8.7% = 0.617 / 7.13 and 24.5% = 1.75 / 7.13, where 7.13 is the average ADE rate among complex patients.
[27] 11.2% = 0.691 / 6.15 and 37.4% = 2.3 / 6.15, where 6.15 is the average ADE rate among less complex patients.

is no evidence that the adoption of EMRs (from any vendor) lead to reductions in 30-day mortality for Pneumonia. Most coefficients are not significantly different from zero and the coefficients of three vendors are significant and positive, which suggests an increase in mortality as a consequence of EMR adoption for hospitals adopting those vendors. In the case of CHF, we see reductions in 30-day mortality rates from the adoption of two EMR vendors. The magnitude of the coefficients suggest that the EMRs of these two vendors led to decreases of .8 to 1.3 percentage points in the 30 day mortality rate for this condition among adopting hospitals. There is an increase in the 30-day mortality rate for CHF for one other vendor and no significant effects for the adopters of remaining vendors. For AMI, two vendors are associated with higher mortality rates, one vendor tends to lower mortality, and the remaining vendors have no significant impacts. The p values at the bottom of each column indicate that the vendor effects are jointly significant, and we are able to reject their joint equality. Similar results are found after adjusting for patient complexity as shown in Table A2 in the appendix.[28] Hence, there is little evidence that vendor differences matter for explaining changes in 30-day mortality.

To further illustrate the effects of EMR adoption on cost savings versus patient quality, we construct Figure 6, which plots the vendor-specific coefficients from the regression for average costs of a hospital stay (from Table 5) against the coefficients from the regression for the ADE rate (from Table 6). While only suggestive, this figure shows how the various results for different vendors may fit together. Figure 6 reveals an interesting pattern. Few vendors are able to deliver both cost savings and improved patient quality at the same time. There are few vendors located in the bottom left quadrant of Figure 6. Instead, most vendors who achieve improvements in patient quality (in the form of reduced ADEs) have increased costs as shown in the bottom right quadrant. This reflects more of a pattern of substitution. For these vendors, achieving the increases in patient quality require increased costs.[29]

[28] However, the p values at the bottom of columns in Table A2 show that the vendor effects are not jointly significant for some 30-day mortality outcomes (Pneumonia among complex patients and CHF for less complex patients). We can not reject the joint equality of the coefficients for the 30-day mortality from CHF among less complex patients.

[29] A few vendors are associated with reduced patient quality (increased ADE rates). The one vendor who is located in the upper right quadrant, however, has a coefficient from the ADE rate regression that is not significantly different from zero, while another vendor with a significantly positive coefficient from the ADE rate does not have a significant coefficient from the costs regression.

6.3 EMR impact on quantity of care

EMRs were also expected to streamline workload and perhaps improve productivity in the provision of hospital care. EMRs could improve productivity if hospitals can treat more patients or provide more services. However, if the use of EMRs interferes with physician practice and makes seeing patients more difficult by health professionals, they may see fewer patients or order fewer procedures.[30]

To explore these different possibilities, we consider how EMR adoption affects two measures of hospital workload, the log of the number of inpatient stays and the log of the number of procedures used for Medicare patients. We use the number of inpatient stays in a particular hospital in a given year, which comes from the MedPAR File.[31] We use the total number of inpatient procedures for a hospital in a given year also using data from the MedPAR File.[32]

We estimate inpatient hospital stays and inpatient procedures as a function of local demographic variables and hospital fixed effects. Local demographics are likely to be a good predictor of hospital patient flows (Billings et al., 1993; Laditka et al., 2003).[33] We merge our datasets with US census data and extract the following variables from the 2000 US Census: population, percentage black, percentage hispanic, percentage over 65, percentage who are $20 - 64$, percentage with a university education, and the median household income. We then link these variables with each hospital by county. These demographic variables will control for regional variation that could help explain the number of inpatient hospital stays and the number of procedures used in a hospital. We further interact these variables with a linear time trend to control for changes in the local environments over time.

We first test for common pre trends among adopters and non adopters without vendor heterogeneity. Figures 5, which presents the coefficients for the treatment group trend prior to EMR

[30] If EMRs cause physicians to lose valuable time with patients, by spending more time interacting with a complex, difficult to use EMR system, then they may not be able to treat as many patients as they did prior to EMR adoption.

[31] Each observation in MedPAR is an inpatient hospital stay. We aggregate the number of inpatient stays for a particular hospital in a given year.

[32] Each observation in MedPAR has the number of procedures ordered by a health professional during an inpatient's hospital stay. We use the aggregate number of procedures.

[33] Since the demographic variables are highly collinear with our hospital characteristics (i.e. hospital admissions and births), we exclude these hospital characteristics from the estimation of visits and procedures, but retain the hospital fixed effects.

adoption, shows that the coefficients are not significantly different than zero for each workload measure. We tested the joint significance of the pre period coefficients (by outcome) and could not reject that they were jointly zero (see first column of Table 3). With vendor heterogeneity, we then test for whether the coefficients of the interaction terms for the adopters of our baseline vendor, Meditech, are jointly zero for the years prior to adoption. The results (column 2 in Table 3) show that we can not reject the premise of a common pre trend among our baseline vendor, Meditech, and the control group (non adopters) for total inpatient stays and total procedures. Hence, possible endogeneity due to the timing of EMR adoption does not pose a threat to our research design. We then test for whether the coefficients of the interaction terms for each alternative vendor are significantly different than the coefficients for our baseline vendor, Meditech, in the pre period. Results (column 3 in Table 3) show that the pre trends for most EMR vendors are not significantly different from our baseline vendor, Meditech, for inpatient stays. For total procedures, coefficients for less than half of the vendors (5/12) are not significantly different from Meditech. Hence, possible endogeneity due to the choice of vendor may limit our ability to draw a causal inference about the effects of a hospital's vendor choice on the total number of procedures.

Results from the general adoption regression (without vendor heterogeneity) are presented in the bottom row of Table 4. Results show that EMR adoption has a positive and significant impact on the number of inpatient stays, but no significant impact on the number of procedures. This provides some mixed evidence about the effects of EMR adoption on hospital workload measures.

Table 8 presents the regression results (with vendor heterogeneity) for the number of inpatient stays in column one and the number of procedures used on Medicare inpatients in column two. The results show heterogeneous effects of EMR adoption on hospital workload. Hospitals who adopted certain EMR vendors saw increases in hospital stays and procedures after EMR adoption, while hospitals who adopted other EMR vendors saw either reductions or no change in hospital stays and procedures. There are two vendors who have positive and significant coefficients in column one, which suggests that EMR adoption of those vendors led to an increase in the number of inpatient stays. There are two other vendors who have negative and significant coefficients, which suggests that EMR adoption led to a decline in inpatient stays. In column two, there are two vendors who have positive and significant coefficients, which suggests that EMR adoption led to an increase

in the number of procedures used on Medicare inpatients. There are three vendors who have negative and significant coefficients, which suggests that EMR adoption led to fewer procedures for Medicare patients. The results show that there is no uniform impact of EMR adoption on hospital workload measures and that the choice of vendor matters to hospitals. The p values at the bottom of each column indicate that the vendor effects are jointly significant and we can reject their joint equality in each regression.

To provide further insight about how the adoption of different EMR vendors affects quantity of care delivered versus quality of patient care, Figure 7 plots the vendor-specific coefficients from the regression for the number of inpatient stays from Table 8 against the coefficients from the regression for the ADE rate from Table 6 column 1. While only suggestive, this figure helps illustrate how the various results for different vendors fit together. Figure 7 shows that there are several vendors for which the adoption of the EMR technology resulted in increases in quantity of care delivered and improvements in patient quality. The bottom right quadrant shows five vendors who were able to deliver both more inpatient stays and reduced ADE rates. However, as in Figure 6, not all vendors are able to deliver gains in both areas. The bottom left quadrant shows vendors whose products led to reduced ADEs, but fewer inpatient stays. For adopting hospitals, the vendor's EMR technology was able to deliver improved patient quality, but with lower patient volume. The results depicted in Figures 6 and 7 suggest that the EMRs from different vendors pose different trade offs to hospitals.

6.4 Robustness Tests

To check the robustness of these results, we perform our analyses using an alternative definition of EMR adoption that allows for the use of different advanced components. For these tests, we define EMR adoption as a hospital who has installed any of the advanced components, CPOE or PD. We maintain a focus on advanced components given their potential to reduce medical or drug-related errors and improve patient quality of care, but this definition allows us to capture the effects advanced EMR components more generally. Figure A1 shows that the proportion of hospitals who adopt either advanced component is higher than in Figure 1. Hospitals who adopted EMRs (defined

as either CPOE or PD) increased from 5.77% in 2006 to 36.7% in 2010. We continue to focus on a hospital's initial EMR adoption decision during our sample period to better identify the effect of the health IT on hospital performance. The results from all our robustness tests are reported in the appendix.

We begin with our common pre trends tests among adopters and non adopters. Without vendor heterogeneity, Figures A2, A3, A4, and A5 show that there are no significant pre trends (for the treated group) among the outcome variables under our alternative adoption definition. We tested the joint significance of the pre period coefficients (by outcome) and could not reject that they were all jointly zero. The p values for these tests are reported in the first column of Table A3. Hence, we can not reject the premise of common pre trends among treatment and control groups under our alternative adoption definition. We next allow for vendor heterogeneity and examine the two dimensions of differential trends using our two part test. The results in column 2 of Table A3 like those in Table 3 show that we can not reject the premise of a common pre trend among our baseline vendor, Meditech, and the control group (never adopters) for all outcome variables using the alternative adoption definition. This suggests that possible endogeneity due to the timing of adoption (of the most common vendor) does not pose a threat to our research design. Results in column 3 of Table A3 show that the pre trends for most EMR vendors are not significantly different from our baseline vendor, Meditech, for the outcome variables. Unlike Table 3, the coefficients for most vendors are not significantly different for the AMI mortality outcome (8 rather than 5) and the number of procedures (9 rather than 5). This provides stronger evidence that possible endogeneity from the choice of vendor does not threaten our research design for these measures. However, it remains possible that since a few vendors pre trends are different from Meditech, we cannot perfectly preclude the endogeneity in vendor choice, conditional on adoption.

Table A4 shows that the results of general EMR adoption on our hospital outcomes without vendor heterogeneity are similar to those previously reported in Table 4 for our primary outcomes.[34] EMR adoption has no significant impact on average hospital costs per inpatient stay, average hospital expenses, CMI, ADE rates, and the three condition-specific 30-day mortality rates (CHF, PN,

[34]The number of observations is smaller using the alternative definition, because there are fewer never adopters and more hospitals whose initial adoption of PD occurred prior to the sample period and are hence excluded.

and AMI). One difference is that the coefficient for total inpatient stays is not significant using the alternative definition of adoption. Without vendor heterogeneity, the results suggest that EMR adoption of advanced components produces no costs savings, quality of care benefits, or workload changes for adopting hospitals.

Table A5 shows that the results of EMR adoption on financial outcomes with vendor heterogeneity are also similar to those reported in Table 5. There are heterogeneous effects following the EMR adoption of different vendors on average hospital costs. The coefficients for two EMR vendors have negative and significant coefficients, which suggests costs savings (ranging from 4.2% to 7.8%) in adopting hospitals. The coefficients for three other vendors are positive and significant, which indicates cost increases (ranging from 3.4% to 6.5%) for adopting hospitals. There are no significant effects of EMR adoption on average hospital costs for remaining vendors. Results in the second column show fewer significant effects of EMR adoption on hospital expenses than in Table 5. We see a reduction in the average hospital expenses (5.4%) from the adoption of one vendor, increases in average hospital expenses (3.7%) from the adoption of one other vendor, and no significant effects on hospital expenses from the adoption of remaining vendors. Results in the third column show more significant effects of EMR adoption on the CMI or the costliness of the Medicare patient mix in hospitals with the alternative definition than in Table 5. We see reductions in the CMI (ranging from 1.5% to 4.7%) from the adoption of four vendors, which suggests a decline in the costliness of the Medicare patient mix for adopting hospitals. We see an increase in the CMI (1.9%) from the adoption of one other vendor, which suggests an increase in the costliness of the Medicare patient mix in adopting hospitals. There are no significant effects of EMR adoption on the CMI for remaining vendors. The p values at the bottom of columns indicate that we can reject that the vendor effects are jointly zero and that the vendor effects are jointly equal at conventional significance levels for average hospital costs and the CMI. This further confirms that the choice of vendor affects EMR performance on these dimensions. Only some vendors deliver on the promise of cost savings, while others result in either increased costs or no change in hospital costs. A difference from Table 5 is that we can't reject that the vendor effects are jointly zero or jointly equal for average hospital expenses using the alternative definition.

Table A6 shows that the results of EMR adoption on ADE rates with and without adjustment

for complexity using the alternative adoption definition are similar to Table 6. Without adjustment for complexity, EMR adoption reduces the rate of ADEs for the adopters of four vendors. The magnitude of the reduction in the ADE rate is also roughly similar ranging from .61 to 2.1 percentage points for these vendors and suggests improvements in patient outcomes for the hospitals who adopted these vendors. We see an increase in the ADE rate for the users of two vendors ranging from .35 to .40 percentage points, and no significant effects for the adopters of remaining vendors. Results in column 2 of Table A6 show reduced ADE rates for complex patients arising from the adoption of EMRs from four vendors and range from .72 to 2.0 percentage points. An increase in the ADE rate is also observed for the adopters of two vendors for complex patients and ranges from .26 to .47 percentage points. Among less complex patients, the EMRs from four vendors lead to reductions in ADE rates ranging from .57 to 2.1 percentage points. Only one vendor is significantly associated with an increase in the ADE rate, with no significant effects of EMR adoption observed for remaining vendors. The p values at the bottom of each column indicate that the vendor effects are jointly significant, and we are able to reject their joint equality. Vendor effects continue to matter for explaining changes in ADE rates with the alternative adoption definition.

Table A7 shows that the results of EMR adoption by vendor on 30-day morality rates for Pneumonia, CHF, and AMI with the alternative adoption definition are mostly similar to Table 7. Results provide little evidence that the adoption of EMRs lead to reductions in 30-day mortality. For Pneumonia, most coefficients are not significantly different from zero and the coefficients of three vendors are significant and positive rather than negative, which suggests an increase in mortality as a consequence of EMR adoption for hospitals adopting those vendors. Only one vendor is associated with a slight reduction in the mortality rate for Pneumonia. A similar pattern is observed for the morality rates from CHF in column two with the coefficients for most vendors not significantly different from zero and three vendors with positive coefficients rather than negative. Only one vendor is associated with a slight reduction in the 30 day mortality rate for CHF. The p values at the bottom of the table suggest that we can reject that the coefficients are jointly zero and jointly equal for Pneumonia and CHF mortality rates. None of the coefficients for AMI mortality are significantly different from zero in the third column.

Table A8 presents the results of EMR adoption on the two workload outcomes with vendor

heterogeneity. There continue to be heterogeneous effects of EMR adoption on hospital workload as in Table 8. However, more hospitals saw a reduction in inpatient stays as a consequence of EMR adoption of select vendors than in Table 8. There are five vendors who have negative and significant coefficients in column one, which suggests that EMR adoption led to a decline in inpatient stays. There is one vendor who has a positive and significant coefficients in column one, which suggests that EMR adoption of that vendor led to an increase in the number of inpatient stays. The results for procedures are more similar to those in Table 8. There are two vendors who have positive and significant coefficients in column two, which suggests that EMR adoption led to an increase in the number of procedures used on Medicare inpatients. There are three vendors who have negative and significant coefficients, which suggests that EMR adoption led to fewer procedures for Medicare patients. The p values at the bottom of each column indicate that the vendor effects are jointly significant and we can reject their joint equality in each regression.

Overall, the resulting effects of EMR adoption of either advanced component (with and without vendor heterogeneity) are similar to those found with CPOE.

6.5 Potential Savings from EMR adoption

In this section, we develop an estimate of the potential cost savings that could arise if all hospitals adopted an EMR vendor who could lower hospital costs (or reduce the ADE rate). We first estimate the savings in the cost of routine inpatient hospital care from EMR adoption. Given that not all vendors result in cost savings, our back-of-the-envelope calculation is based on the vendors that generate savings as shown in Table 5 column 1—between 3.60% and 4.92%. On average, the total cost of routine hospital care based on the hospitals in our sample is $232 billion, and the potential savings if all these hospitals adopt the vendors that lower the total cost range from $8.35 billion to $11.4 billion. Considering that our sample accounts for approximately 48% of the total cost of routine hospital care in the U.S., the annual savings range from $17.5 billion to $23.9 billion when extrapolating to the national sample.

We next explore the potential cost savings for hospitals from reducing the ADE rate. The Institute of Medicine's landmark study (Kohn et al., 2000) showed that ADEs not only had serious

implications for patients including disability, higher risk of death, and increased financial burden, but they also posed significant costs for hospitals. Prior studies provided a quantitative estimate of the economic burden from adverse drug events occurring to hospitalized patients (Bates et al., 1997; Classen et al., 1997; Suh et al., 2000; Hug et al., 2012; Poudel et al., 2017), with the additional direct costs attributable to ADEs ranging from $1,049 - $3,234 per patient (Marques et al., 2016). Drawing upon this literature and using our results from Table 6, we develop an estimate of the cost savings from reduced ADEs that come from the adoption of certain EMR vendors.

We calculate our measure of cost savings as follows. In our data, there are, on average, 720,856 hospitalized patients with ADEs per year. We rely on the estimate of the direct cost per patient attributable to ADEs in Poudel et al. (2017), $1,851, because they use a similar set of ICD-9 codes to define ADEs and base their analysis on a national inpatient database in the U.S. in a similar period. Multiplying the number of hospitalized patients with ADEs times the direct cost of an ADE per patient produces total direct costs of ADEs equal to $1.33 billion among hospitalized Medicare patients per year. To calculate the reduction in the ADE rate due to EMR adoption among our vendors, we consider the coefficients in Table 6 column 1. Considering only the vendors that produced a significant reduction in the ADE rate, the coefficients range from a reduction of 0.67 to 1.67 percentage points in the ADE rate. We then multiply these coefficients times the number of patients (720,856) to get the reduction in the number of patients having ADEs and then multiply this product times the cost per ADE ($1851). This yields an annual direct savings from reduced ADEs that range from $8.9 million to $22.3 million among the Medicare inpatient population, if hospitals adopt the EMR systems of vendors that are able to effectively lower ADEs. Considering that Medicare accounts for about 27.7% of total spending on hospital care between 2006-2010, the estimated total savings in the hospital sector due to reduced ADEs range from $32.2 million to $80.4 million per year.[35]

This is likely to be a conservative estimate for two reasons. First, the estimated direct costs per patient in Poudel et al. (2017) is based on patients at all ages, whereas the cost associated with ADEs among the Medicare population is likely higher given that Medicare patients may represent

[35]This percentage is taken from the table of national health expenditure downloaded from CMS. See: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NHE-Fact-Sheet.

a sicker population with more underlying conditions, have greater exposure to medication-related errors, and be faced with more costs incurred from ADEs. Moreover, our calculation has not accounted for any cost savings from shortened hospital stay, reduced mortality rates, and fewer emergency department visits due to less incidence of ADEs, which could be substantial.[36]

7 Conclusion

Although the U.S. government has invested heavily in promoting HIT, there is little systematic evidence showing that the technology is producing the anticipated cost savings or improvements in patient outcomes. Previous research has not accounted for the possibility that differences in the products made by competing HIT vendors may contribute to differences in product performance. Our study compares the effect of EMR adoption on hospital performance outcomes with and without vendor heterogeneity and examines how the differences among vendors affects EMR performance in U.S. hospitals.

Our results suggest that the differences among the EMR vendors matter for assessing the effects of EMR adoption on hospital performance. Without vendor heterogeneity, we find no significant effect of EMR adoption on hospital costs or quality of care outcomes for patients. With vendor heterogeneity, results show reductions in the cost of providing inpatient hospital care (ranging from 3.6% to 4.9%) from the adoption of two vendors, increases in inpatient costs (ranging from 3.5% to 16.7%) from the adoption of three vendors, and no significant effects from the adoption of other vendors. Only hospitals who adopted EMRs from some, but not all vendors, led to cost savings. We observe similar variability for the other financial measures, average hospital expenses and the case-mix index. For patient outcomes, we also find that the adoption of EMRs from some, but not all, vendors led to improvements in patient quality, namely the rate of adverse drug events. Results show that EMR adoption reduces the rate of adverse drug events (ADEs) between 0.67% and 1.7% for the users of four vendors, increases the rate of ADEs by 0.3% for the users of one vendor, and has no significant effects for the adopters of other vendors.[37]

[36] For instance, prior studies suggested that the occurrence of ADEs generally increases the length of stay by 1.7 to 2.2 days and mortality rates by 2.4% (Piontek et al., 2010).

[37] Freedman et al. (2018) found that EMR adoption reduced preventable ADEs in a younger population of patients.

We found that few vendors deliver both cost savings and improved patient quality at the same time for adopting hospitals. For the adopters of most vendors, achieving improvements in patient quality requires increased costs and reflects more of a pattern of substitution. In addition, many, but not all, vendors could deliver improved patient quality along with increases in quantity for adopting hospitals. For some vendors, however, improved patient quality only came with a reduction in quantity. Our results suggest that there are consequences and trade offs to hospitals of adopting different EMR vendors.

Our results help explain why past studies such as Agha (2014) found little or no evidence of cost savings or mixed evidence of quality of care improvement arising from EMR adoption. The effects may have been masked because they did not account for vendor heterogeneity and the fact that cost savings and patient quality improvements only arise for the users of some vendors. Our estimates suggest that if all in-sample hospitals adopt EMR vendors who lower the ADR rate, they could experience annual direct savings that range from $8.9 million to $22.3 million among the Medicare inpatient population. Annual savings from reduced ADEs could range from $32.2 million to $80.4 million per year when extrapolating to the national sample. We also estimate that if all the in-sample hospitals adopt the vendors that lower the average hospital costs, they could achieve annual savings that range from $8.35 billion to $11.4 billion. The annual savings could range between $17.5 billion and $23.9 billion when extrapolating to the national sample.

There are some caveats to our study. First, the omission of hospitals who switched EMR vendors during our period of study may remove some hospitals who were not satisfied with their EMR systems. If such switchers were motivated by poor EMR vendor performance, then our cost savings estimates may reflect an upward bias. However, we believe that any such bias would be minimal given that (i) there are relatively few hospitals that fall into this category and (ii) there are other reasons why hospitals may switch vendors beside poor performance, such as desire for compatibility with a hospital system or higher than expected costs of maintenance or upgrades. Second, our data on EMR adoption does not allow us to examine how specific meaningful use requirements and

We show that these results extend to Medicare patients as well, but only for the users of select EMR vendors. The result points to the role of decision support from particular EMR vendors as a channel through which patient benefits emerge as suggested by Freedman et al. (2018), and suggests EMRs may help improve care coordination and information management for patients as argued in McCullough et al. (2016).

their evolution over time impact EMR performance. Future research with additional years of data can better examine these effects. Third, our study only included certain patient outcome measures that have received much attention in the literature. Future research could evaluate the effects of vendor heterogeneity on a richer or more diverse set of patient outcomes, such as the complication rates for medical conditions, to better assess EMR performance in hospitals.

An important policy implication of our study is that the government's certification standards for EMRs and eligibility criteria for subsidies (to adopt EMRs) are not sufficient for ensuring that all EMR systems deliver cost savings and/or improved quality of care. The variability in EMR performance among vendors shown in our study suggests that there is a hidden cost to the government's standards. Providers will not learn about these costs until after substantial investments in HIT are made. Policymakers should inform providers (ex ante) about product differences among the vendors or take stronger steps to ensure that certified EMRs are delivering cost savings or improved patient care.

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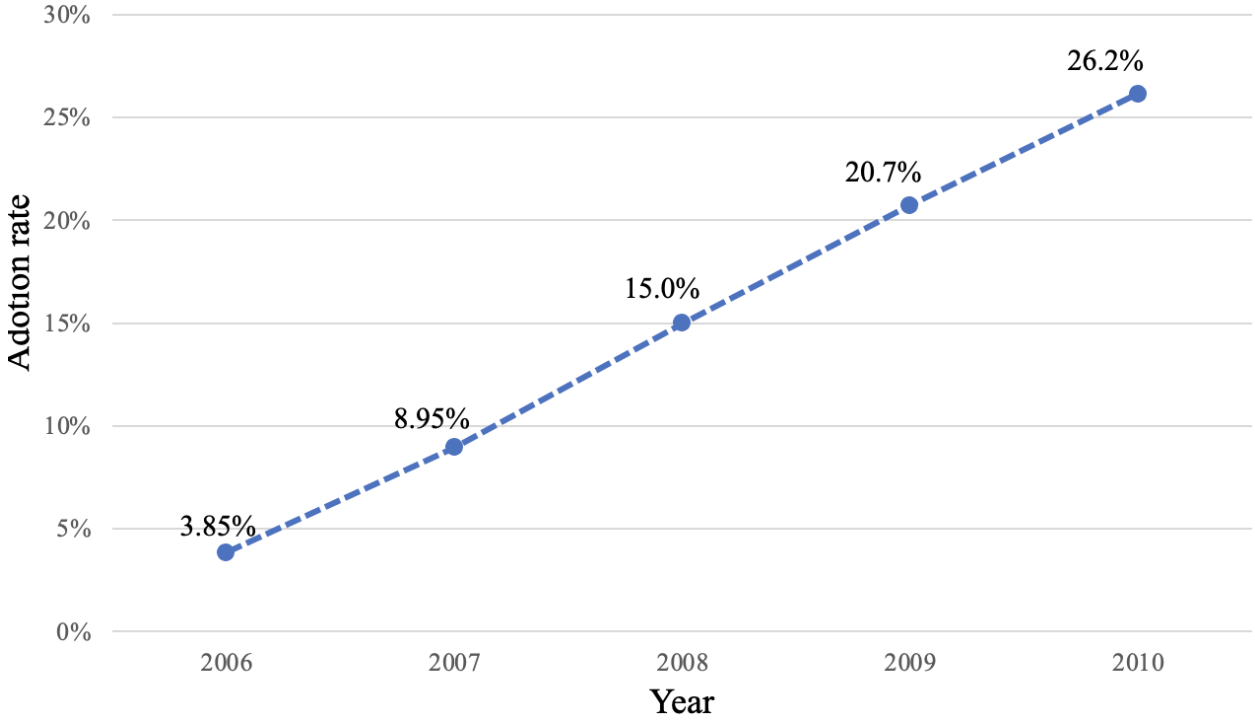
Figure 1: Adoption rate over time



Note: This figure displays the adoption rate of initial adopters of CPOE.

Figure 2: Trends of financial outcomes between adopters and non-adopters

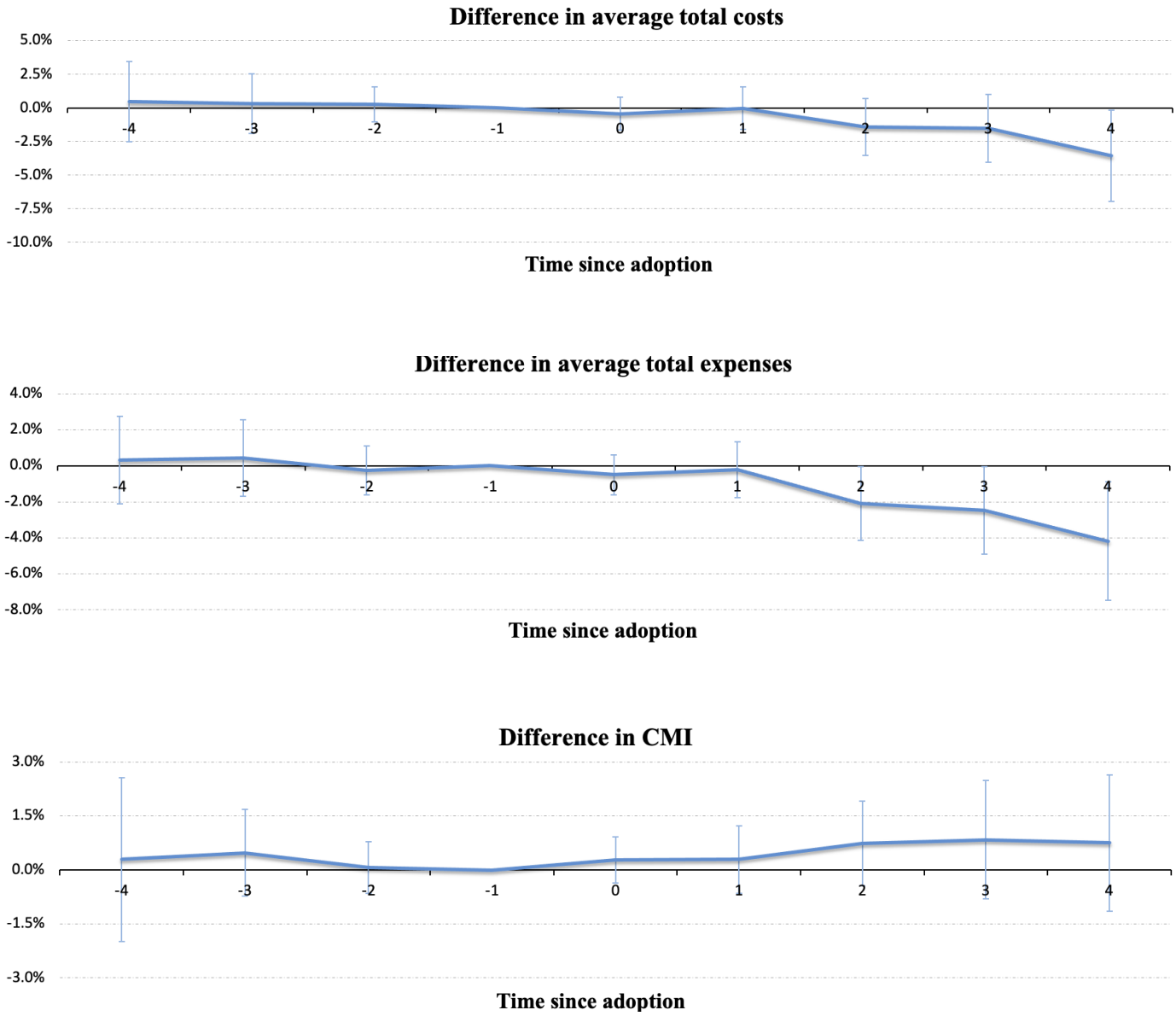


Figure 3: Trends of ADE rates between adopters and non-adopters

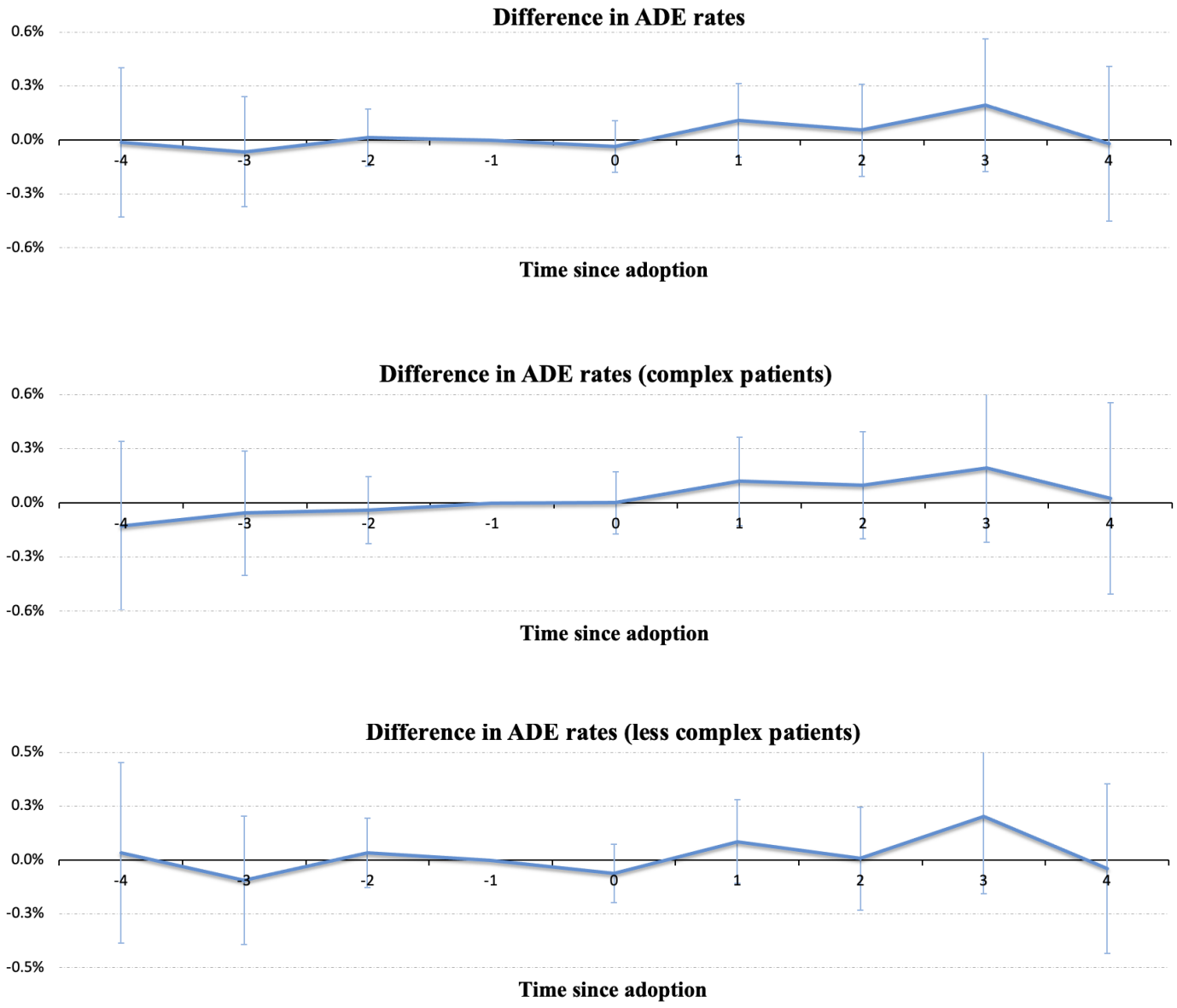


Figure 4: Trends of mortality rates between adopters and non-adopters

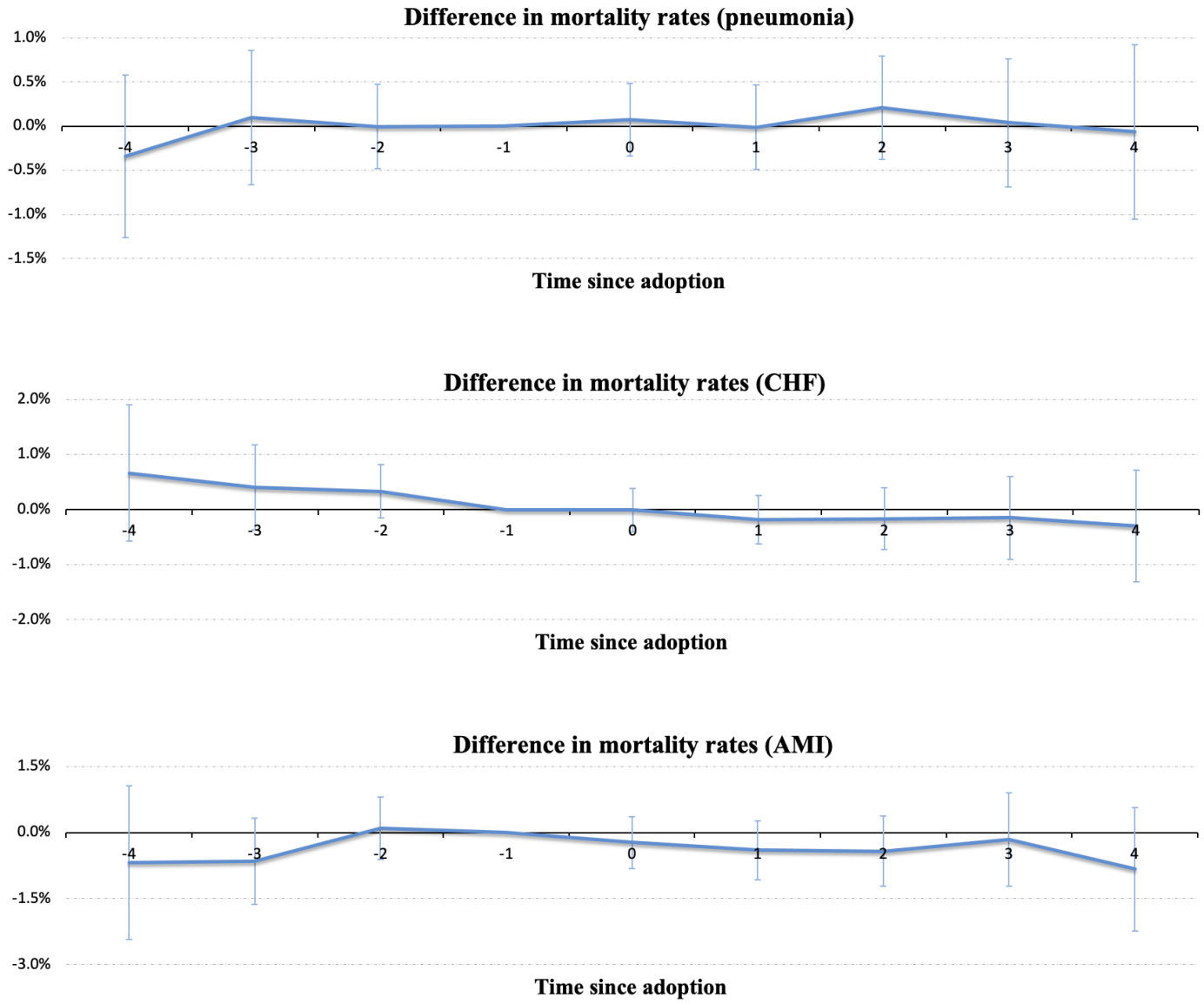


Figure 5: Trends of variables on hospital workload between adopters and non-adopters

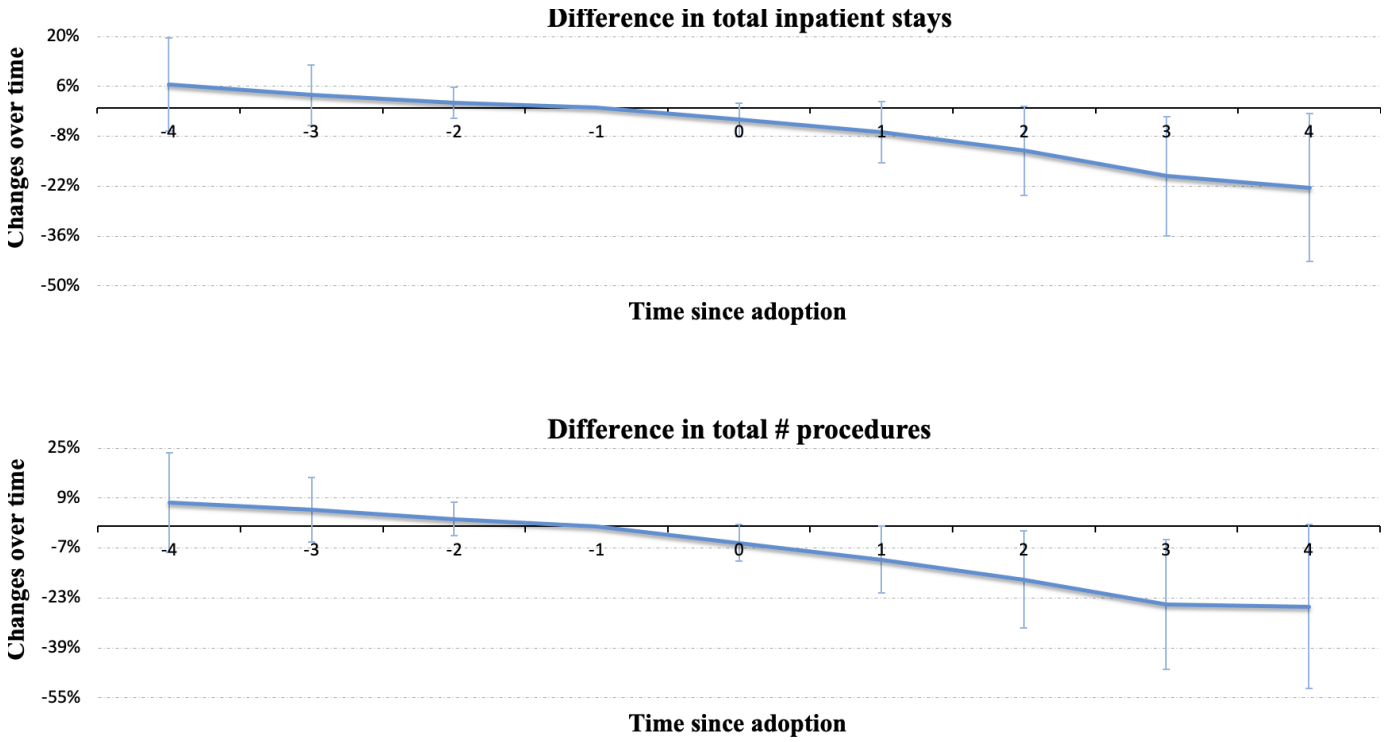


Figure 6: ADE rates vs. average hospital costs per stay

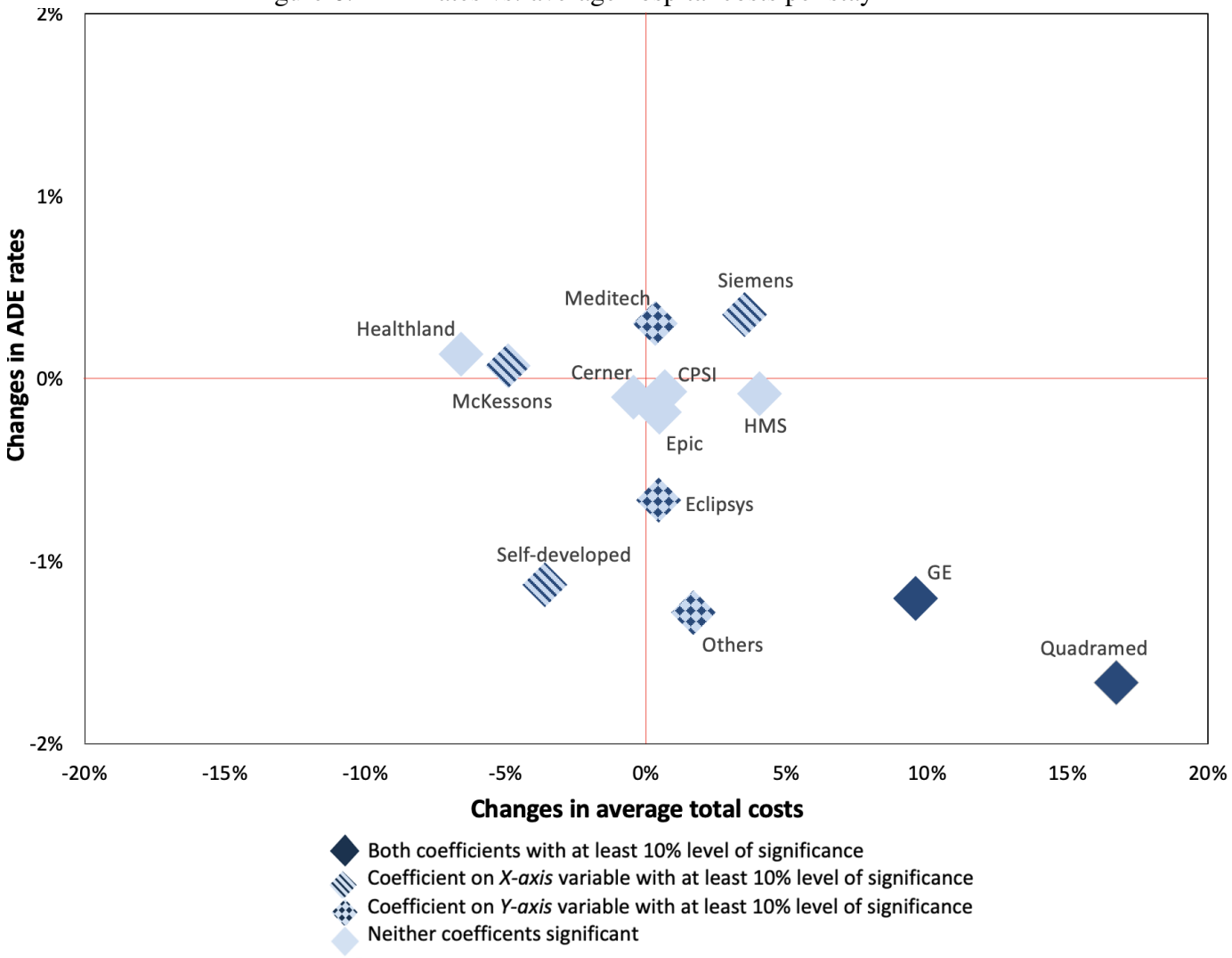


Figure 7: ADE rates vs. total inpatient stays

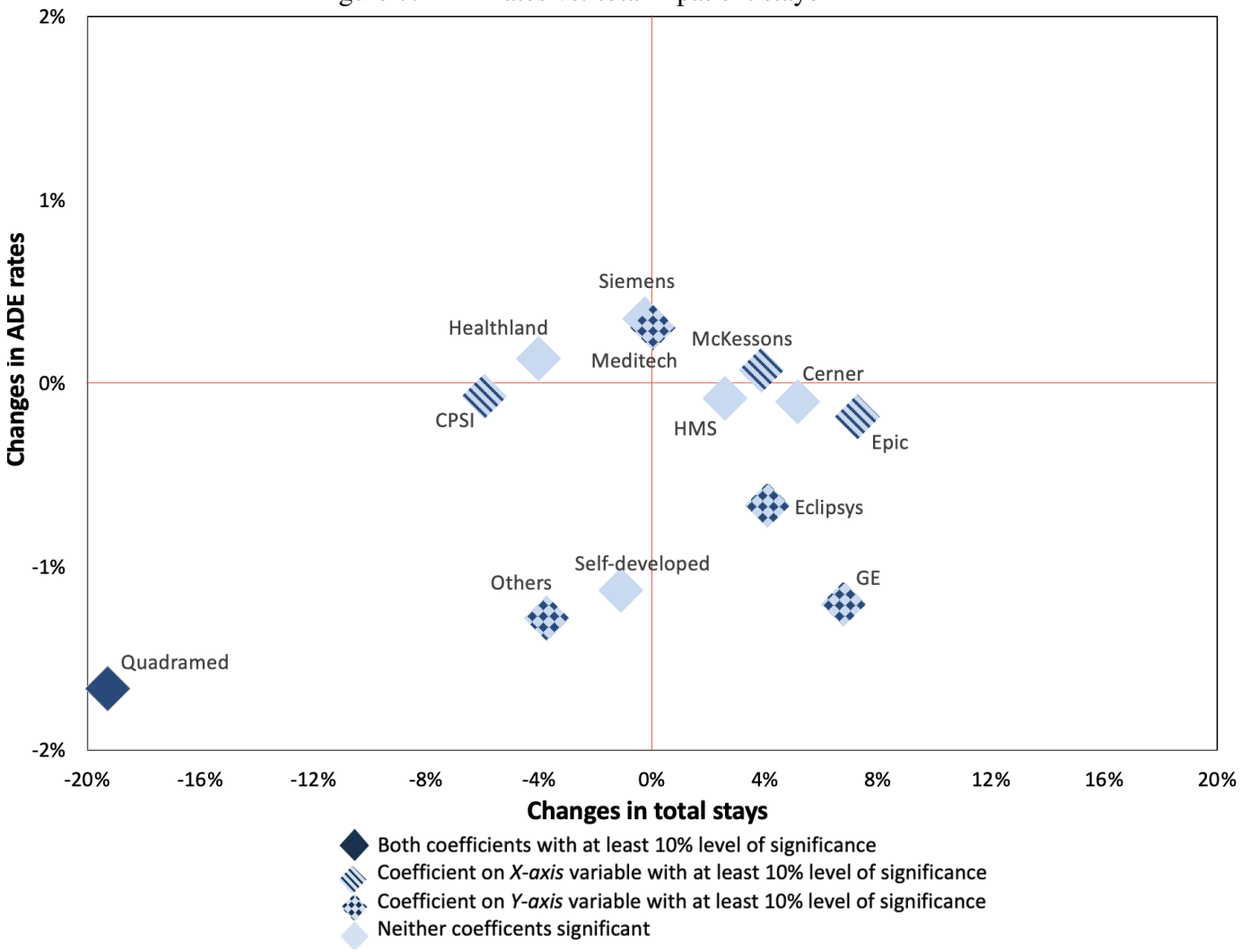


Table 1: Summary statistics for outcome variables

	2006	2007	2008	2009	2010	# Obs.
Financial measures						
Average costs per stay ($)	12,832	13,548	14,131	14,990	16,011	13,650
Average expenses per stay ($)	18,564	19,905	20,842	21,900	23,820	16,195
CMI	1.19	1.20	1.22	1.24	1.24	16,262
ADE rates (%)						
All patients	5.50	5.91	6.32	8.70	6.44	16,258
Complex patients	5.95	6.38	6.97	9.32	7.04	16,239
Less complex patients	5.14	5.52	5.84	8.24	6.00	16,250
Mortality rate (%)						
Pneumonia	12.7	12.1	12.2	11.6	10.9	16,020
CHF	14.0	14.0	14.1	13.3	12.8	15,637
AMI	19.8	19.3	19.0	17.9	16.5	13,727
Hospital workload						
Total inpatient stays	2,289	2,251	2,399	2,406	2,468	16,262
Total # procedures	3,209	3,148	3,379	3,409	3,534	16,262

Note: Table reports the mean value by year. Source: Medicare Provider Analysis and Review (MedPar) File.

Table 2: Summary statistics for hospital characteristics by adoption status

Variable	Total	Non-adopters	Adopters (pre-adoption)
Staffed beds	143	129	186
Outpatient visits	101,404	89,560	137,866
Admissions	6,023	5,263	8,361
Births	693	596	992
Inpatient days	33,491	29,517	45,725
% of Medicare discharge	49.9	50.7	47.3
% of Medicaid discharge	16.4	16.4	16.6
For-profit hospitals	0.197	0.225	0.114
Not-for-profit hospitals	0.573	0.548	0.652
Equity model hospital	0.019	0.019	0.016
Foundation hospital	0.042	0.046	0.029
Independent practice - - association hospital	0.147	0.151	0.136
Management service - - organization hospital	0.070	0.069	0.073
Residency or Member of - - Council Teaching Hospitals	0.037	0.027	0.067
Affiliated to a hospital system	0.551	0.557	0.531
Critical access hospitals	0.310	0.336	0.233
# hospitals	3,593	2,712	881
# Obs.	14,000	12,115	1,885

Note: Table reports the mean value across the years 2006-2010. Note that the total number of observations does not add up to 16,262, the number of observations in our main analysis, because the summary statistics here exclude the post-adoption period for adopters. Data for hospital characteristics come from the American Hospital Association (AHA) Annual Survey.

Table 3: Summary of pre-adoption trend analysis

	P values on joint insignificance of pre-adoption periods (*adopters* vs. *non-adopters*)	*P* values on joint insignificance of pre-adoption periods (*Meditech users* vs. *non-adopters*)	# out of 12 vendors that are NOT significantly different from *Meditech*
Financial measures			
Average costs per stay	0.973	0.963	10
Average expenses per stay	0.878	0.920	9
CMI	0.849	0.585	9
ADE rates			
All patients	0.884	0.752	10
Complex patients	0.948	0.442	9
Less complex patients	0.547	0.969	9
Mortality rate			
Pneumonia	0.818	0.837	9
CHF	0.457	0.752	9
AMI	0.526	0.426	5
Hospital workload			
Total inpatient stays	0.771	0.111	8
Total # procedures	0.788	0.318	5

Table 4: General adoption effects

Financial measures	Average costs per stay	Average expenses per stay	CMI
Adopt	-0.00334	-0.00330	0.00235
	(0.00688)	(0.00641)	(0.00380)
N	13,650	16,195	16,262
ADE rates	All patients	Complex patients	Less complex patients
Adopt	0.000154	0.000604	-0.000166
	(0.000837)	(0.000988)	(0.000775)
N	16,258	16,239	16,250
Mortality rates	Pneumonia	CHF	AMI
Adopt	0.000609	-0.00196	-0.00259
	(0.00189)	(0.00177)	(0.00265)
N	16,020	15,637	13,727
Hospital workload	Total inpatient stays	Total # procedures	
Adopt	0.0246**	0.00892	
	(0.0107)	(0.0148)	
N	16,159	15,434	

Note: For outcome measures other than hospital workload, other regressors include hospital fixed effects, state-year fixed effects, an indicator for whether it was ever a critical access hospital interacted with a linear time trend, and the value of the following hospital controls in 2006 interacted with a linear time trend: bed size, total admissions, total births, percentage of Medicare discharges, percentage of Medicaid discharges, profit status, system affiliation status, whether it is an independent physician association hospital, whether it is organized as a management service organization, whether it is in a foundation model, whether it is in an equity model, and whether it is a teaching hospital. For outcome measures on hospital workload, we replace the hospital controls with an adopter-specific time trend and the following demographic controls valued in 2006 interacted with a linear time trend: population size, percentage with at least a university education, the median household income, percentage black, percentage hispanic, percentage over 65, and percentage who are 20 – 64. We weight each observation by the number of total visits at the hospital level. Clustered standard errors in parentheses.

$* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$

Table 5: Vendor-specific effects — financial measures

	Average costs per stay	Average expenses per stay	CMI
Self-developed	-0.0360*	-0.0104	-0.00850
	(0.0209)	(0.0161)	(0.0133)
Cerner	-0.00440	-0.0156	0.0166*
	(0.0136)	(0.0174)	(0.00872)
CPSI	0.00663	0.0172	-0.0114
	(0.0260)	(0.0181)	(0.00808)
Healthland	-0.0657	-0.0678*	-0.0247**
	(0.0660)	(0.0357)	(0.0111)
Eclipsys	0.00443	-0.0103	0.0184
	(0.0151)	(0.0153)	(0.0171)
Epic	0.00466	-0.00919	-0.00621
	(0.0250)	(0.0232)	(0.0110)
GE	0.0959*	0.0452	-0.0296
	(0.0541)	(0.0366)	(0.0228)
HMS	0.0404	0.0533*	-0.0182
	(0.0433)	(0.0303)	(0.0152)
McKessons	-0.0492***	-0.0259**	0.00268
	(0.0149)	(0.0126)	(0.00857)
Siemens	0.0350**	0.0351**	-0.00654
	(0.0141)	(0.0139)	(0.0111)
Meditech	0.00324	0.00389	0.00176
	(0.0111)	(0.0104)	(0.00658)
Quadramed	0.167**	0.146	-0.0471***
	(0.0732)	(0.115)	(0.0129)
Others	0.0168	0.0149	0.0106
	(0.0559)	(0.0666)	(0.0164)
N	13,650	16,195	16,262
P-value for joint insignificance	0.00240	0.0303	0.00817
P-value for joint equality	0.00142	0.0204	0.0101

Notes: Other regressors follow the same specification as in Table 4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Vendor-specific effects — ADE rates

	All patients	Complex patients	Less complex patients
Self-developed	-0.0113	-0.0107	-0.0119*
	(0.00743)	(0.00818)	(0.00703)
Cerner	-0.00105	-0.000399	-0.00133
	(0.00225)	(0.00269)	(0.00202)
CPSI	-0.000725	-0.000591	-0.000306
	(0.00325)	(0.00375)	(0.00322)
Healthland	0.00131	0.00226	-0.00179
	(0.00605)	(0.00720)	(0.00576)
Eclipsys	-0.00669**	-0.00617*	-0.00691**
	(0.00296)	(0.00345)	(0.00272)
Epic	-0.00185	-0.00202	-0.00169
	(0.00217)	(0.00247)	(0.00206)
GE	-0.0121***	-0.0120***	-0.0137***
	(0.00422)	(0.00453)	(0.00438)
HMS	-0.000855	-0.00256	-0.000444
	(0.00338)	(0.00510)	(0.00274)
McKessons	0.000672	0.000734	0.000604
	(0.00183)	(0.00217)	(0.00171)
Siemens	0.00348	0.00270	0.00386*
	(0.00243)	(0.00297)	(0.00224)
Meditech	0.00301**	0.00428***	0.00214*
	(0.00131)	(0.00149)	(0.00126)
Quadramed	-0.0167***	-0.00865	-0.0230***
	(0.00206)	(0.0110)	(0.00868)
Others	-0.0128***	-0.0175**	-0.00915*
	(0.00471)	(0.00721)	(0.00468)
N	16,258	16,239	16,250
P-value for joint insignificance	1.95e-14	0.00512	0.000378
P-value for joint equality	2.97e-13	0.00325	0.000222

Notes: Other regressors follow the same specification as in Table 4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Vendor-specific effects — condition-specific mortality rates

	Pneumonia	CHF	AMI
Self-developed	0.0249	0.0476	0.0414**
	(0.0381)	(0.0394)	(0.0161)
Cerner	-0.00447	0.00574	-0.0110*
	(0.00455)	(0.00349)	(0.00563)
CPSI	0.0134*	0.00759	-0.0231
	(0.00730)	(0.00884)	(0.0216)
Healthland	-0.0111	0.0172	0.0593
	(0.0126)	(0.0167)	(0.0456)
Eclipsys	0.00298	-0.000221	0.000627
	(0.00608)	(0.00529)	(0.00970)
Epic	0.00974*	-0.00501	0.00493
	(0.00529)	(0.00511)	(0.00637)
GE	-0.00143	-0.00404	-0.00993
	(0.00920)	(0.00708)	(0.0160)
HMS	0.00188	0.0158	0.0449
	(0.0202)	(0.0223)	(0.0382)
McKessons	0.000604	-0.00781**	-0.00468
	(0.00392)	(0.00382)	(0.00492)
Siemens	-0.00560	-0.0127**	-0.00459
	(0.00539)	(0.00635)	(0.00964)
Meditech	-0.000457	-0.00221	-0.000561
	(0.00337)	(0.00281)	(0.00406)
Quadramed	0.0794***	0.0596***	0.0195**
	(0.0212)	(0.0113)	(0.00835)
Others	-0.0198	-0.00448	-0.0106
	(0.0188)	(0.0246)	(0.0255)
N	16,020	15,637	13,727
P-value for joint insignificance	0.0191	0.0000234	0.0539
P-value for joint equality	0.0139	0.0000117	0.0371

Notes: Other regressors follow the same specification as in Table 4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Vendor-specific effects — hospital workload

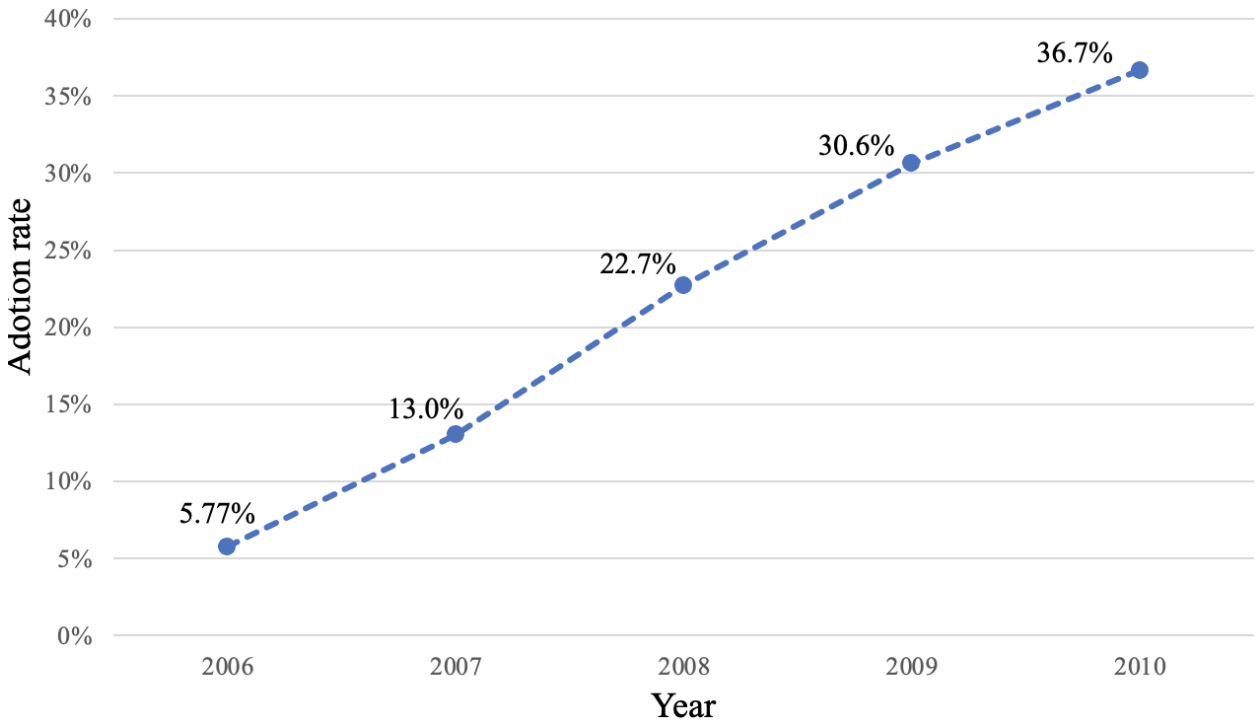
	Total inpatient stays	Total # procedures
Self-developed	-0.0109	-0.0581**
	(0.0338)	(0.0283)
Cerner	0.0517	0.0311
	(0.0323)	(0.0408)
CPSI	-0.0594***	-0.0990**
	(0.0204)	(0.0472)
Healthland	-0.0402	-0.0694
	(0.0407)	(0.0860)
Eclipsys	0.0409	0.00119
	(0.0365)	(0.0523)
Epic	0.0728***	0.0627**
	(0.0254)	(0.0312)
GE	0.0679	0.0456
	(0.0535)	(0.0548)
HMS	0.0260	0.0940
	(0.0565)	(0.0789)
McKessons	0.0388**	0.0491**
	(0.0193)	(0.0246)
Siemens	-0.00258	-0.0809*
	(0.0205)	(0.0414)
Meditech	0.000308	-0.00974
	(0.0156)	(0.0195)
Quadramed	-0.193***	-0.143
	(0.0453)	(0.102)
Others	-0.0372	0.0755
	(0.0463)	(0.0760)
N	16,262	15,570
P-value for joint insignificance	0.00000339	0.00693
P-value for joint equality	0.00000182	0.00421

Notes: Other regressors follow the same specification as in Table 4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix I: Extra figures and tables

Figure A1: Adoption rate over time (*alternative* adoption definition)



Note: This figure displays the adoption rate of initial adopters of CPOE or PD.

Figure A2: Trends of financial outcomes between adopters and non-adopters (*alternative* adoption definition)

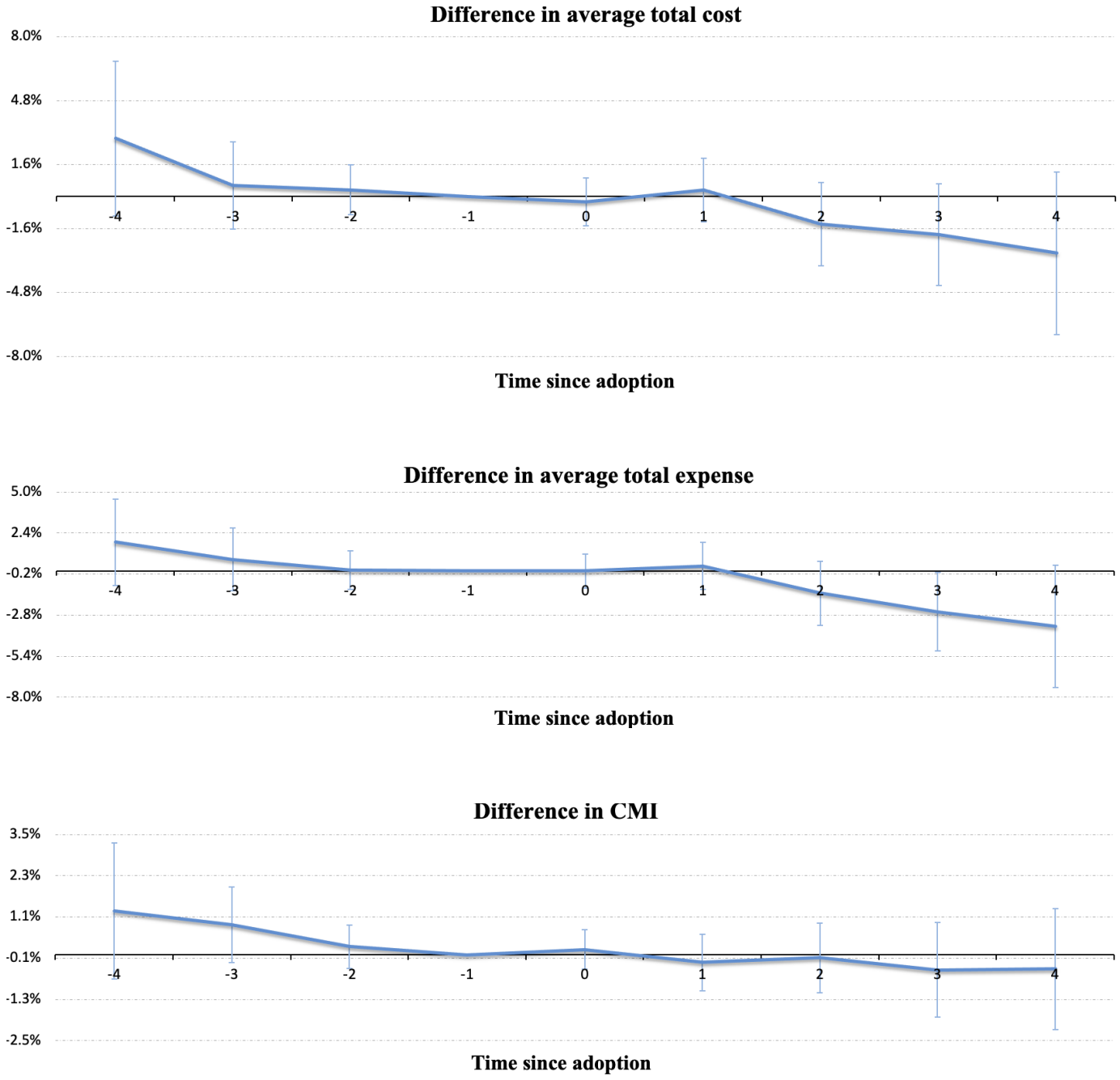


Figure A3: Trends of ADE rates between adopters and non-adopters (*alternative* adoption definition)

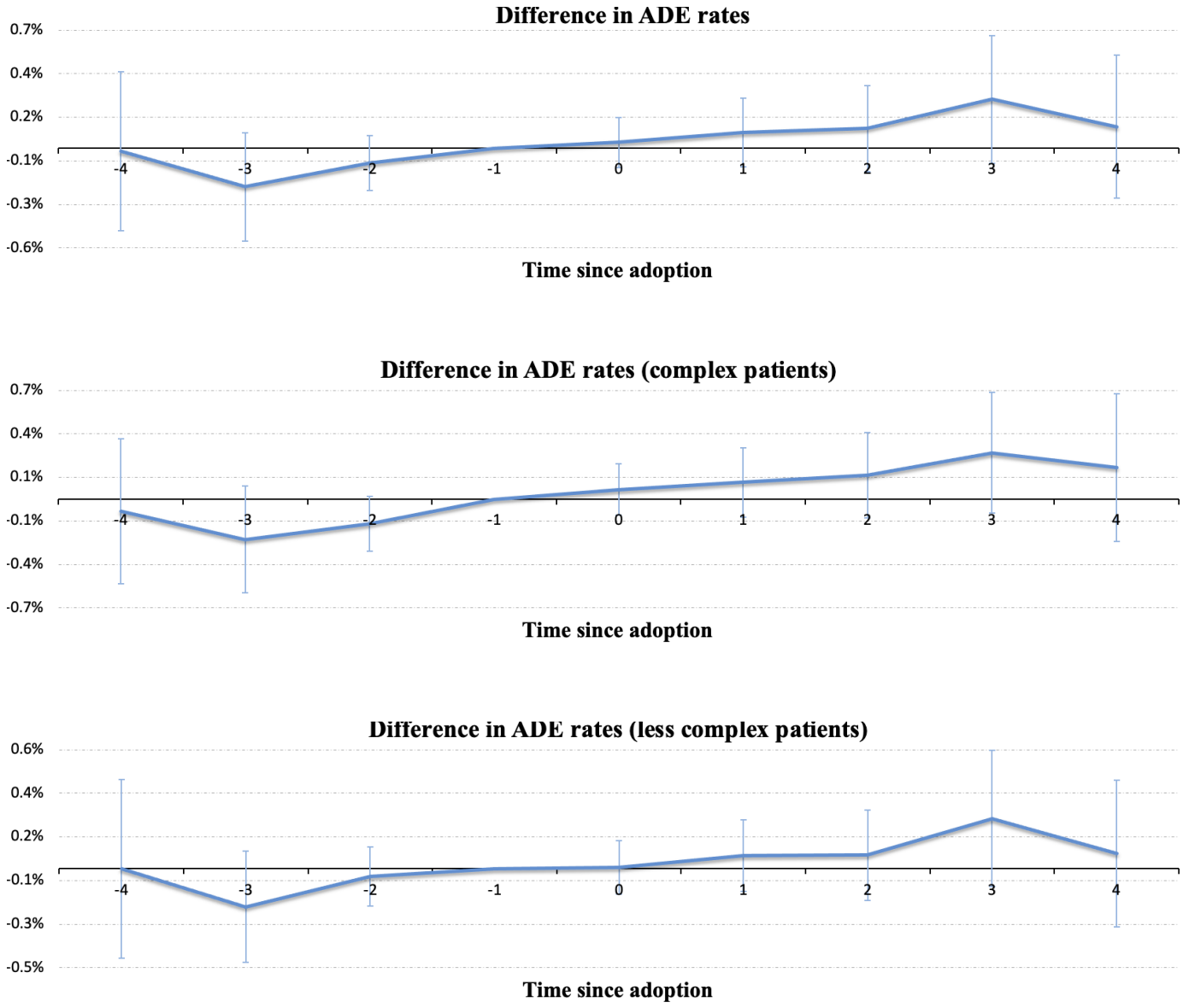


Figure A4: Trends of mortality rates between adopters and non-adopters (*alternative* adoption definition)

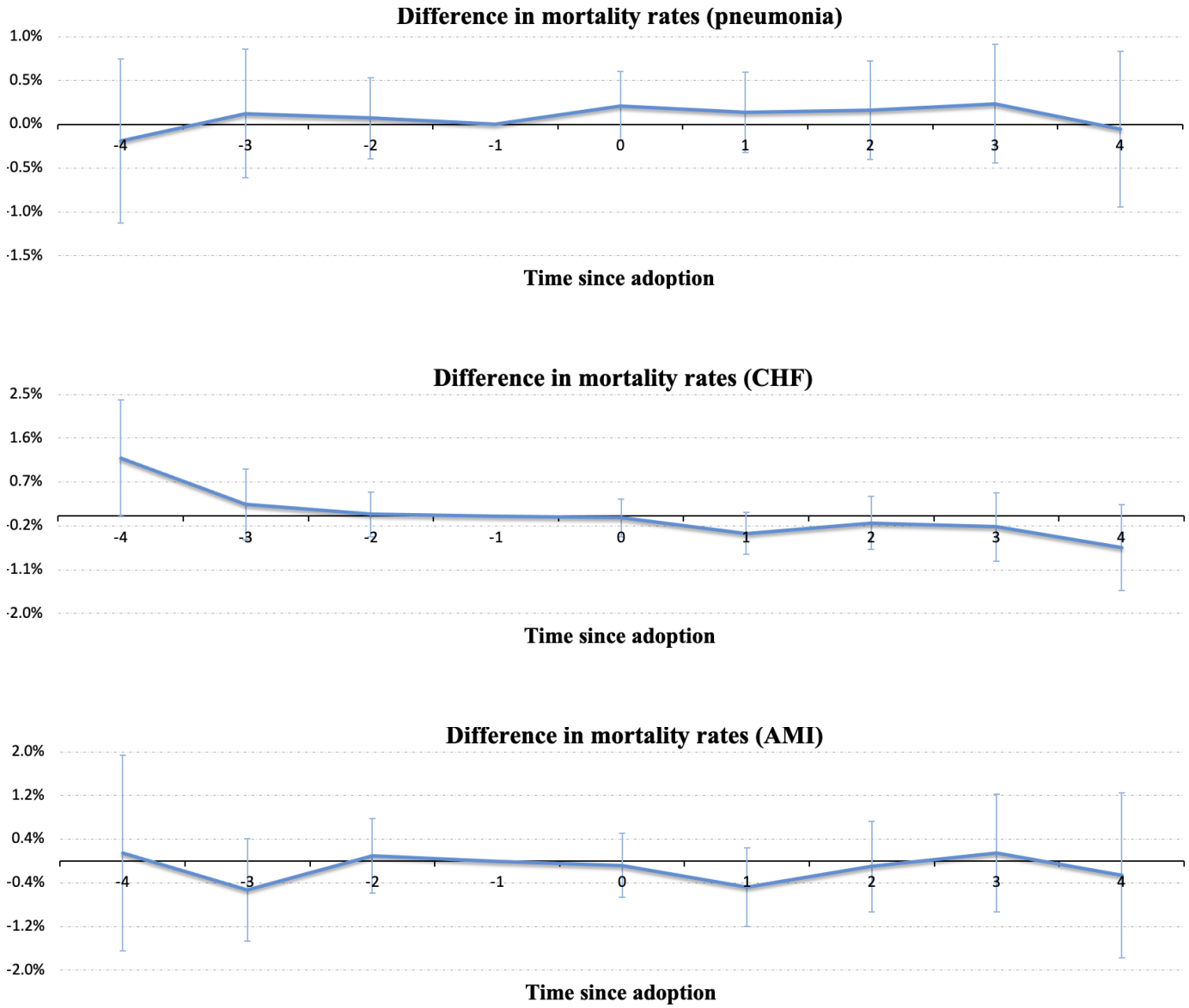


Figure A5: Trends of variables on hospital workload between adopters and non-adopters (*alternative* adoption definition)

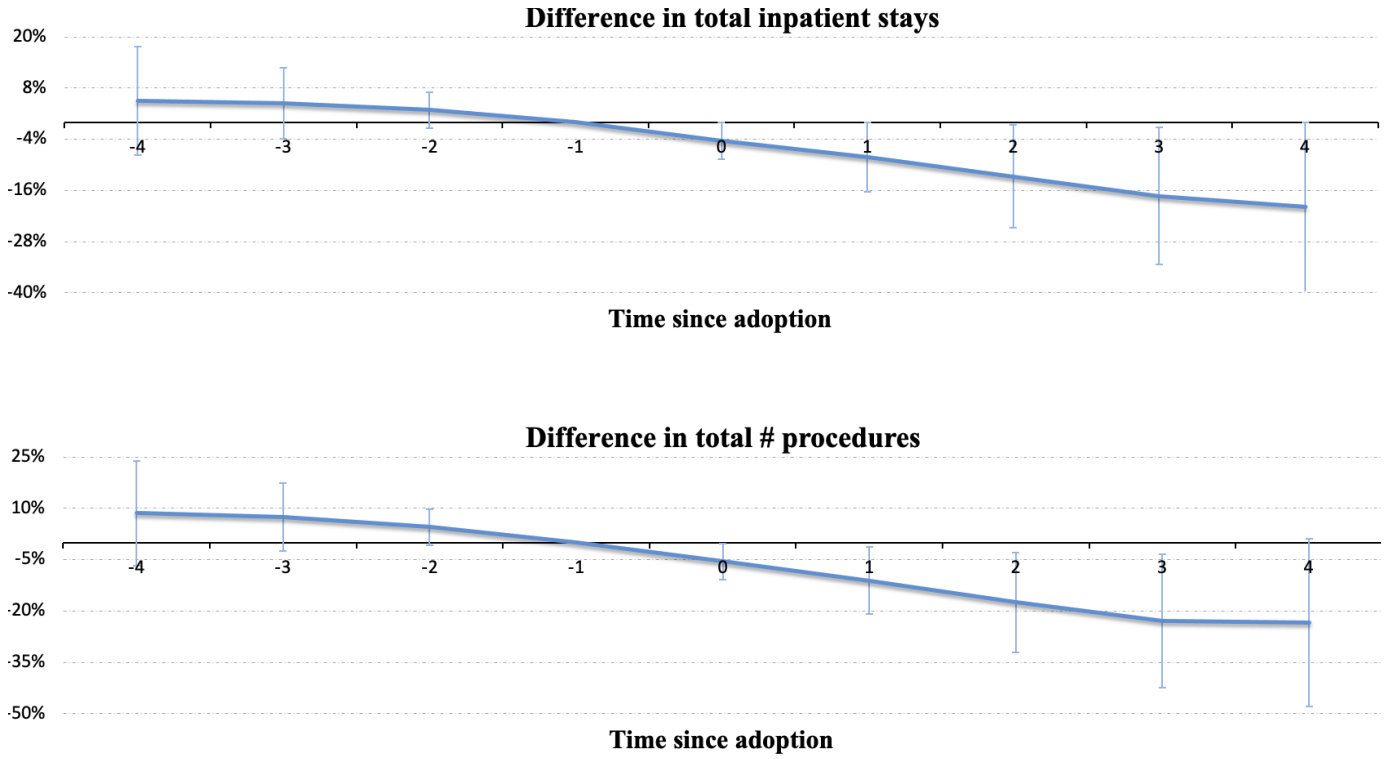


Table A1: ICD-9 codes for diseases considered in mortality

Disease	ICD-9 codes
Pneumonia	480–486, 487.0
CHF	428.0–428.9
AMI	410.0–410.9

Table A2: Vendor-specific effects — condition-specific mortality rates by complexity

	Complex patients			Less complex patients		
	Pneumonia	CHF	AMI	Pneumonia	CHF	AMI
Self-developed	0.0303	0.0486	0.0856***	0.0183	0.0419	0.0483
	(0.0332)	(0.0374)	(0.0146)	(0.0397)	(0.0436)	(0.0514)
Cerner	-0.00128	0.00636	-0.00584	-0.00676	0.00421	-0.0107
	(0.00625)	(0.00466)	(0.00963)	(0.00614)	(0.00504)	(0.00693)
CPSI	0.0280**	0.0141	-0.0406	0.00295	0.00182	-0.0174
	(0.0134)	(0.0114)	(0.0342)	(0.00958)	(0.0127)	(0.0282)
Healthland	0.00214	0.000855	-0.00972	-0.0207	0.0273	0.0711***
	(0.0175)	(0.0369)	(0.0879)	(0.0168)	(0.0264)	(0.0267)
Eclipsys	0.00596	0.0164*	-0.0000964	0.00297	-0.0155**	0.00665
	(0.0107)	(0.00882)	(0.0177)	(0.00495)	(0.00675)	(0.00872)
Epic	0.0100	-0.00239	0.0223**	0.00953*	-0.00709	0.00229
	(0.00802)	(0.00707)	(0.0111)	(0.00575)	(0.00597)	(0.00719)
GE	-0.0107	0.0155	-0.0121	0.00501	-0.0284**	-0.0250
	(0.0118)	(0.00966)	(0.0381)	(0.0105)	(0.0141)	(0.0168)
HMS	0.0182	0.0801***	0.119	0.00721	0.00708	0.0546
	(0.0204)	(0.0270)	(0.101)	(0.0223)	(0.0315)	(0.0377)
McKessons	-0.000727	-0.00279	-0.00716	0.00432	-0.00930**	-0.00461
	(0.00524)	(0.00518)	(0.0130)	(0.00463)	(0.00457)	(0.00616)
Siemens	-0.0138	-0.0232***	-0.00712	-0.00165	-0.00122	0.00414
	(0.00854)	(0.00884)	(0.0135)	(0.00623)	(0.00642)	(0.0115)
Meditech	-0.00227	-0.00197	-0.000533	0.000251	-0.000186	-0.00127
	(0.00510)	(0.00409)	(0.00804)	(0.00375)	(0.00341)	(0.00498)
Quadramed	0.118**	0.0735***	-0.168***	0.0440***	-0.00243	0.170***
	(0.0458)	(0.0103)	(0.0123)	(0.0120)	(0.0379)	(0.0357)
Others	-0.0289	-0.0305	-0.0323	-0.0155	0.0211	0.0246
	(0.0342)	(0.0312)	(0.0486)	(0.0183)	(0.0225)	(0.0487)
N	15482	14897	11184	15703	14930	12556
P-value for joint insignificance	0.127	6.24e-11	5.42e-42	0.0559	0.152	0.000248
P-value for joint equality	0.0917	2.26e-10	2.54e-39	0.0668	0.199	0.000132

Notes: Other regressors follow the same specification as in Table 4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Summary of pre-adoption trend analysis (*alternative* adoption definition)

	P values on joint insignificance of pre-adoption periods (*adopters* vs. *non-adopters*)	*P* values on joint insignificance of pre-adoption periods (*Meditech users* vs. *non-adopters*)	# out of 12 vendors that are NOT significantly different from *Meditech*
Financial measures			
Average costs per stay	0.519	0.897	8
Average expenses per stay	0.590	0.692	8
CMI	0.412	0.712	10
ADE rates			
All patients	0.398	0.747	7
Complex patients	0.254	0.756	7
Less complex patients	0.393	0.551	8
Mortality rate			
Pneumonia	0.910	0.505	9
CHF	0.272	0.305	7
AMI	0.569	0.708	8
Hospital workload			
Total inpatient stays	0.509	0.541	7
Total # procedures	0.309	0.414	9

Table A4: General adoption effects (*alternative* adoption definition)

	Average costs per stay	Average expenses per stay	CMI
Adopt	-0.000428	0.00254	-0.000600
	(0.00655)	(0.00593)	(0.00345)
N	12101	14630	14697
ADE rates			
	All patients	Complex patients	Less complex patients
Adopt	0.000786	0.00129	0.000411
	(0.000789)	(0.000928)	(0.000743)
N	14695	14680	14686
Mortality rates			
	Pneumonia	CHF	AMI
Adopt	0.00165	-0.00137	-0.00214
	(0.00181)	(0.00176)	(0.00278)
N	14469	14095	12219
Hospital workload			
	Total inpatient stays	Total # procedures	
Adopt	-0.00230	-0.00563	
	(0.00981)	(0.0131)	
N	14697	13998	

Note: For outcome measures other than hospital workload, other regressors include hospital fixed effects, state-year fixed effects, an indicator for whether it was ever a critical access hospital interacted with a linear time trend, and the value of the following hospital controls in 2006 interacted with a linear time trend: bed size, total admissions, total births, percentage of Medicare discharges, percentage of Medicaid discharges, profit status, system affiliation status, whether it is an independent physician association hospital, whether it is organized as a management service organization, whether it is in a foundation model, whether it is in an equity model, and whether it is a teaching hospital. For outcome measures on hospital workload, we replace the hospital controls with an adopter-specific time trend and the following demographic controls valued in 2006 interacted with a linear time trend: population size, percentage with at least a university education, the median household income, percentage black, percentage hispanic, percentage over 65, and percentage who are 20 – 64. We weight each observation by the number of total visits at the hospital level. Clustered standard errors in parentheses.

$* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$

Table A5: Vendor-specific effects — financial measures (*alternative* adoption definition)

	Average costs per stay	Average expenses per stay	CMI
Self-developed	-0.0114	0.00646	-0.0206**
	(0.0309)	(0.0185)	(0.0100)
Cerner	0.00905	0.00618	0.0191**
	(0.0127)	(0.0148)	(0.00795)
CPSI	0.0172	0.0258	-0.0145*
	(0.0252)	(0.0170)	(0.00770)
Healthland	-0.0784*	-0.0544*	-0.0277***
	(0.0431)	(0.0306)	(0.00780)
Eclipsys	0.0335*	0.0120	0.0165
	(0.0184)	(0.0231)	(0.0202)
Epic	-0.0113	-0.0192	-0.00758
	(0.0223)	(0.0244)	(0.0119)
GE	0.0646*	0.0148	-0.0136
	(0.0369)	(0.0284)	(0.0183)
HMS	0.0248	0.0103	-0.0110
	(0.0247)	(0.0254)	(0.0132)
McKessons	-0.0421***	-0.0115	0.00369
	(0.0156)	(0.0127)	(0.00827)
Siemens	0.0342**	0.0367**	-0.0134
	(0.0148)	(0.0154)	(0.0103)
Meditech	0.00276	0.00105	-0.00169
	(0.0105)	(0.0103)	(0.00596)
Quadramed	0.0199	0.0347	-0.0465***
	(0.0429)	(0.0491)	(0.0152)
Others	0.000867	-0.00468	0.0119
	(0.0343)	(0.0367)	(0.0112)
N	12101	14630	14697
P-value for joint insignificance	0.0222	0.363	0.000142
P-value for joint equality	0.0222	0.354	0.000572

Notes: Other regressors follow the same specification as in Table A4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Vendor-specific effects — ADE rates (*alternative* adoption definition)

	All patients	Complex patients	Less complex patients
Self-developed	-0.00439	-0.00337	-0.00574**
	(0.00280)	(0.00329)	(0.00257)
Cerner	0.00346*	0.00468*	0.00291
	(0.00209)	(0.00245)	(0.00190)
CPSI	0.00112	0.000908	0.00155
	(0.00324)	(0.00375)	(0.00310)
Healthland	-0.00488	-0.00717**	-0.00413
	(0.00315)	(0.00362)	(0.00369)
Eclipsys	-0.00833*	-0.00883	-0.00792**
	(0.00451)	(0.00568)	(0.00387)
Epic	-0.00168	-0.00172	-0.00161
	(0.00234)	(0.00259)	(0.00226)
GE	-0.00761**	-0.00752*	-0.00849**
	(0.00364)	(0.00398)	(0.00369)
HMS	0.00313	0.000922	0.00410
	(0.00246)	(0.00290)	(0.00294)
McKessons	0.00246	0.00281	0.00211
	(0.00179)	(0.00209)	(0.00168)
Siemens	0.00404*	0.00415	0.00405**
	(0.00225)	(0.00276)	(0.00206)
Meditech	0.00154	0.00264*	0.000762
	(0.00121)	(0.00139)	(0.00119)
Quadramed	-0.0206**	-0.0199**	-0.0211**
	(0.00947)	(0.0100)	(0.00966)
Others	-0.00611*	-0.00987**	-0.00320
	(0.00364)	(0.00482)	(0.00342)
N	14695	14680	14686
P-value for joint insignificance	0.00183	0.00299	0.00139
P-value for joint equality	0.00121	0.00204	0.000842

Notes: Other regressors follow the same specification as in Table A4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Vendor-specific effects — mortality rates (*alternative* adoption definition)

	Pneumonia	CHF	AMI
Self-developed	0.00581	0.00418	-0.00385
	(0.00790)	(0.00868)	(0.0114)
Cerner	0.00139	0.00251	-0.00564
	(0.00429)	(0.00364)	(0.00531)
CPSI	0.0175***	0.00999	-0.000113
	(0.00652)	(0.00851)	(0.0197)
Healthland	-0.0180	0.0276**	0.0341
	(0.0119)	(0.0125)	(0.0461)
Eclipsys	0.000294	0.00240	-0.00310
	(0.00922)	(0.00753)	(0.0141)
Epic	0.00953*	-0.00651	0.00493
	(0.00520)	(0.00540)	(0.00704)
GE	-0.00173	0.00172	0.00164
	(0.00669)	(0.00896)	(0.0159)
HMS	0.00329	0.0205*	0.0293
	(0.0106)	(0.0110)	(0.0222)
McKessons	0.00270	-0.00673*	-0.000268
	(0.00386)	(0.00399)	(0.00560)
Siemens	-0.00517	-0.00812	-0.000485
	(0.00490)	(0.00652)	(0.00838)
Meditech	0.000579	-0.00282	-0.00595
	(0.00319)	(0.00278)	(0.00426)
Quadramed	0.0344**	0.0435***	-0.00835
	(0.0148)	(0.0144)	(0.0294)
Others	-0.0445**	-0.0231	-0.0319
	(0.0200)	(0.0169)	(0.0196)
N	14469	14095	12219
P-value for joint insignificance	0.0173	0.00743	0.788
P-value for joint equality	0.0183	0.00468	0.810

Notes: Other regressors follow the same specification as in Table A4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Vendor-specific effects — hospital workload (*alternative* adoption definition)

	Total inpatient stays	Total # procedures
Self-developed	-0.0916***	-0.148***
	(0.0230)	(0.0314)
Cerner	0.0380	0.0262
	(0.0274)	(0.0336)
CPSI	-0.0837***	-0.153***
	(0.0188)	(0.0486)
Healthland	-0.109***	-0.0202
	(0.0279)	(0.0801)
Eclipsys	-0.0131	-0.0307
	(0.0480)	(0.0586)
Epic	0.0558**	0.0565*
	(0.0274)	(0.0342)
GE	0.0197	0.00845
	(0.0440)	(0.0468)
HMS	-0.0424	-0.0176
	(0.0359)	(0.0490)
McKessons	0.0217	0.0440**
	(0.0184)	(0.0216)
Siemens	-0.0324*	-0.0759**
	(0.0185)	(0.0305)
Meditec	-0.0136	-0.00495
	(0.0137)	(0.0159)
Quadramed	-0.0527	-0.0526
	(0.0504)	(0.0596)
Others	-0.0755*	0.0402
	(0.0397)	(0.0629)
N	14697	13998
P-value for joint insignificance	4.59e-08	0.00000406
P-value for joint equality	0.000000320	0.00000298

Notes: Other regressors follow the same specification as in Table A4 or are as described in Page 14 in the main text. Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$