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

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Abstract

Although the government has invested billions to encourage the adoption of health information technology in hospitals, there is little evidence showing that it is producing the expected efficiencies such as cost savings and improved quality of care. Based on a national sample of hospitals, we examine whether vendor heterogeneity can help explain this puzzle. We find that the effect of electronic medical records (EMRs) on hospital costs and quality outcomes varies substantially by vendor. Not all certified EMR vendors lead to cost savings or improvements in quality of care for adopting hospitals. While a few vendors deliver both cost savings and improved quality of care, other vendors who deliver improvements in care quality do so with increased hospital costs, reflecting a pattern of substitution. If all the in-sample hospitals were to adopt vendors that lower hospitalization costs three or more years after adoption, we estimate annual savings ranging from $6.18 billion to $31.9 billion, and $12.8 billion and $66.5 billion when extrapolating to the national sample. Our findings raise questions about whether government certification standards for EMR vendors are sufficient to ensure benefits for adopting hospitals and suggest that there is a hidden cost to the government's standards.

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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 care. 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.

EMRs are complex software systems and vendors have discretion to develop and differentiate their respective EMR systems. Product heterogeneity could lead to variation in product capabilities or system quality and affect system performance. For instance, 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, it requires that vendors only meet a constrained set of functions known to them in advance.[1] Studies have noted variability in certified

[1] See https://www.healthcareitnews.com/news/eclinicalworks-pay-155-million-settle-suit-alleging-it-faked-meaningful-use-certification. In addition, this post also indicates that such testing takes place in more of a controlled setting that is unlikely to reflect conditions of real world use.

EMR systems (Sittig et al., 2015; McCoy et al., 2015; Ratwani et al., 2015; Holmgren et al., 2017), but there has been little study of how such variability impacts actual hospital outcomes.

Examining the impact of EMRs on hospital costs or clinical outcomes is a particularly interesting issue to study. EMRs should 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 EMR vendor heterogeneity may help resolve this puzzle.

This paper examines how the adoption of different EMR vendors affects EMR performance in hospitals. Our analysis exploits the variation among the hospitals who adopt EMRs and non-adopting hospitals, variation in the time since EMR adoption, and variation in the vendors adopted to explore these effects. We examine how EMR adoption affects average inpatient costs per discharge, total inpatient discharges, and adverse drug event rates using data from Medicare Hospital Cost Reports and the Medicare Provider Analysis and Review (MedPAR) File. We identify a hospital's decision to adopt an EMR and its vendor using 2006 to 2017 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 find no evidence of differential pre trends or endogeneity related to EMR adoption decisions. We use a fixed effects model to compare the impact of EMR adoption on hospital 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. We do find, however, that inpatient discharges increase for hospitals who adopted EMRs at least 3 years earlier, which indicates that time since adoption matters for some outcomes. With vendor heterogeneity, results show hospitals who adopted three vendors at least 3 years earlier had reductions in the average inpatient costs (ranging from 2.7% to 14.3%), while hospitals who adopted two other vendors had increases in inpatient costs (ranging from 10.1% to 11.1%). No significant effects were observed for hospitals who adopted other vendors. In addition, hospitals who adopted four vendors' EMRs at least 3 years earlier had increases in inpatient discharges (ranging from 3.3% to 20.3%), while hospitals who adopted another vendor had decreases in the number of discharges (3.3%). No significant effects were observed for remaining vendors. For our measure of care quality, results show that hospitals who adopted four vendors had reductions the rate of adverse drug events (ADEs) (from the time of adoption) ranging from 0.67% and 1.7%, while hospitals who adopted one other vendor saw increases the ADE rate by 0.3%, and hospitals who adopted the remaining vendors had no significant effects.

When taken together, our analyses show that few vendors deliver cost savings, increased patient volume, and improved care quality at the same time for adopting hospitals. Instead, some vendors who achieve improvements in care quality have increased inpatient costs, a pattern reflect-

ing substitution. In addition, only some vendors who deliver improved care quality also treat more inpatients. For other vendors, improvements in care quality are only achieved with fewer inpatient discharges. 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 EMR vendor heterogeneity masks important variability in assessing the effects of those EMRs on hospital performance. Such variability may arise from differences in system capabilities, system quality, or usability. Our analysis and results may also help explain why past studies found little to no evidence of cost savings or quality improvement arising from EMR adoption on average. If all the in-sample hospitals were to adopt vendors that lower hospitalization costs three or more years after adoption, a back-of-the-envelope estimation suggests annual savings would range from $6.18 billion to $31.9 billion and $12.8 billion and $66.5 billion when extrapolating to the national sample.

Our study builds upon prior research that has assessed the impact of HIT in three ways. First, our study examines more hospital EMR adoption decisions including those made in more recent years after the passage of HITECH in 2009.[2] Given that HITECH was designed to increase EMR adoption incentives, it is important to include the adoption decisions made in the years following HITECH to capture the effects of EMR adoption in more hospitals. Second, we show the importance of accounting for EMR vendor heterogeneity in assessing EMR effectiveness. Third, 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 fol-

[2] Agha (2014) examines adoption between 1998 and 2005, while Dranove et al. (2014) studies adoption between 1996 and 2009, McCullough et al. (2016) studies the period 2002-2007, and Freedman et al. (2018) studies the period 2003-2010.

lowing EMR adoption (Agha, 2014; Dranove et al., 2014) and mixed evidence about the impact of HIT adoption on patient outcomes (Miller and Tucker, 2011; Agha, 2014; Haque, 2014; McCullough et al., 2016; 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, more discharges, 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). While differences among vendors' EMRs may offer more choice and flexibility to hospitals, 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 the certification process and HITECH program participation to ensure 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, and discusses how vendor heterogeneity may potentially impact EMR performance in hospitals. 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 their functions

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.[3] 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).

EMRs have the potential to increase efficiency and health care quality in several ways. The technology collects all patient information in one place, including medical history, 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

[3]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.

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, 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.[4] Given the range of possible effects, it becomes even more important to empirically study how the differences among different vendors' EMRs affects hospital performance.

2.2 HITECH Act

The application of information technology in the U.S. health care sector has lagged behind other developed countries (Jha et al., 2008). Only in the last decade or so have health care providers started to pick up this technology, spurred by increased political activity to provide incentives for HIT and the passage of HITECH.

A series of actions taken by President George W. Bush first outlined an incentive 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 number of meetings with the public and private sectors in 2006-2007

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

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 capture 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 objectives. The Centers for Medicare and Medicaid Services (CMS) have adjusted and amended the requirements and deadlines over time to accommodate eligible providers.

EMR vendors have to meet a constrained set of certification criteria specified by the CMS and ONC. This criteria has 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 in an effort to reduce program complexity. Although the MU requirements are designed to ensure that each vendor's system meets a common set of objectives (perhaps representing a lower bar), the incentive program may have led to more innovation and product differentiation among vendors. Holmgren et al. (2017) investigated the extent to which certified vendors are able to meet the government's meaningful use criteria and found substantial variation. It remains to be seen how such variation among vendors' products ultimately impacts hospital and patient outcomes.

2.3 Vendor Heterogeneity and EMR Performance

The EMRs of different vendors may vary in important ways. Prior literature has noted heterogeneity among the EMRs of different vendors in terms of the way that test results and other information are displayed (Sittig et al., 2015), the storage and organization of data, usability and user-centered design that may impact how providers interact with a vendor's system (Ratwani et al., 2015), clinical decision support capabilities (McCoy et al., 2015), customer support, training, and system maintenance among the vendors. Holmgren et al. (2017) suggests that the EMRs of different vendors vary in system architecture, user interface design, and functionality. These differences reflect the ways that vendors may differentiate their products.

There has been little study of the effects of vendor heterogeneity and how that heterogeneity may impact system performance. The national market intelligence firm KLAS began to compile annual HIT vendor rating scores in the late 1990s to help future providers understand how well different vendors' HIT systems perform on various margins.[5] The variability among vendors' EMRs and the users' experiences with those systems may impact physician practice, physician interactions, and potentially affect the delivery of care. For instance, the EMR products from some vendors may be easier to use than the products from other vendors. Some vendors may offer better clinical decision support for their EMRs than other vendors. Some vendors may invest more resources in training for hospital staff to use their products or they may offer better system maintenance. Some vendors' may also design EMR systems to be more easily interoperable with the EMR systems made by other vendors, while other vendors may try to limit interoperability as a

[5]KLAS's annual HIT vendor rating scores are based on the responses of the CIOs of hospitals who are members of HIMSS and other healthcare professionals who adopted different vendors.

way to preserve competitive advantages. The interoperability of one EMR system with another allows for the easy exchange of health data among providers in and between different hospitals. Examples include when hospitals send e-prescriptions to pharmacies or when hospitals want to send or acquire patient data from another hospital. Desai (2016) argues that the rate of electronic information sharing and interoperability among EMRs in hospitals is low and may impact performance in hospitals. Policymakers have argued that EMR systems with increased interoperability may have a higher level of care and patient satisfaction, as well as reduced operational costs. All these differences may potentially affect the way different vendors' systems are implemented and used in hospitals.

Given evidence of vendor heterogeneity, it becomes even more important to assess how those differences may impact EMR performance. Such evidence will allow greater understanding about how differences in EMR funtionality and quality may translate into differences in system performance. For instance, if vendors invest more resources in making their systems **easier for providers to use**, then adopting hospitals may be more likely to experience system efficiencies from improved information sharing and enhanced clinical decision support, which may result in cost savings, improved quality of care, or productivity gains, such as increased patient flow. If vendors have EMR systems that are more difficult for providers to use, then adopting hospitals may find that such systems impede information sharing and the coordination of care. Difficult to use systems could result in either no change or increased patient costs, reduced quality of care, and/or lower patient flows. In addition, if some EMR vendors direct more resources to **customer support, training, and system maintenance**, then adopting hospitals may be more likely to experience efficiencies from enhanced information sharing and improved care coordination. This may also result in provider

cost savings, improved quality of care, or productivity gains, such as increased patient flow. If other EMR vendors direct fewer resources to customer support and system maintenance for their products, then adopting hospitals may be less likely to experience the same system efficiencies. Instead, limited IT or customer support could result in increased hospital costs, poor quality of care, and limited patient flows. Also, if some EMRs are designed for greater **interoperability** with EMRs from other vendors, then adopting hospitals may be more likely to experience system efficiencies from improved information exchange within and between hospitals, which may result in cost savings, improved quality of care, or productivity gains, such as increased patient flow. If other vendors make EMRs less interoperable with other vendors' systems, then adopting hospitals may lack such benefits. These examples suggest that there may be many dimensions to EMR quality. However, we do not observe the disaggregated dimensions of EMR quality by vendor. Instead, our analysis relies on the adopted vendor as a proxy for aggregate EMR quality. With variation in vendors adopted by hospitals, our empirical analysis can then examine the extent to which vendor heterogeneity exists and the extent to which it is associated with differences in EMR performance.

Isolating the effect of vendor heterogeneity on EMR performance will require that we control for any hospital-level characteristics that may also influence performance outcomes. For instance, there may be systematic differences between hospitals such as differences in hospital size, ownership type, teaching status, etc. that may also impact hospitals costs and quality outcomes. To control for such differences, it will be important to include hospital fixed effects to capture the effects of time invariant factors than may also influence hospital outcomes. In addition, it may be important to include other time-varying hospital characteristics since those factors may also influence hospital outcomes. Beyond controlling for hospital characteristics, it is also important

to consider the extent to which EMR adoption or the adoption of a particular vendor is driven by certain hospital characteristics. There could be unobserved hospital characteristics that both influence a hospital's decision to adopt an EMR and affect its outcomes. The presence of such factors may invalidate the assumptions of our proposed analysis, particularly if adopting and non adopting hospitals have differential trends in the outcomes prior to EMR adoption. We will examine this issue by considering the extent to which there are common trends in outcomes for EMR adopters (as well as for the adopters of particular EMR vendors) and non adopters prior to EMR adoption to ensure the validity of our estimation strategy.

3 Data

To examine the effects of vendor heterogeneity on EMR performance in U.S. hospitals in 2006-2017, we use data from the following sources: Hospital Cost Reports (CMS), the Medicare Provider Analysis and Review (MedPAR) File (CMS), the Healthcare Information and Management Systems Society (HIMSS) Analytics Database (HIMSS), and the American Hospital Association (AHA) Annual Survey (AHA).

We examine three different outcome measures. The first is a financial outcome—average inpatient hospital costs —drawn from 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. Our average hospital cost measure represents the cost of providing routine care to treat inpatients. It is constructed by dividing general inpatient routine service costs by the total

number of hospital discharges.[6] We believe that the cost of care for routine inpatient services is most likely to be impacted by the application of health IT. In additional analyses, we consider an alternative cost measure, average operating expenses, which is a broader measure of costs and was examined by Dranove et al. (2014). Using data from Hospital Cost Reports, we calculate average hospital operating expenses by taking the sum of direct costs and salaries across all departments, such as the expenses on plant operations, administrative salaries, utilities, and then dividing by the total number of hospital discharges. This measure will allow us to examine the extent to which EMR adoption may affect a hospital's financial performance in aspects other than the routine inpatient care, such as operation, staffing, and capital depreciation.[7] Our unit of analysis is at the hospital/year level, so each outcome variable is constructed as an annual average across all in-sample inpatients discharged by that hospital in a given year.

The second outcome measure is the number of annual inpatient discharges at a hospital. This measure is also derived from Hospital Cost Reports. The measure allows us to examine the extent to which EMR adoption affected the volume of inpatients seen at a hospital in a given year. EMRs may lead to streamlined workload and improved productivity in the provision of inpatient care, which could allow hospitals to treat more inpatients. However, it is also possible that EMRs may interfere with physician practice and make seeing patients more difficult or cumbersome for health professionals. If true, then EMR adoption could lead doctors to see fewer patients.[8] The third

[6]Routine services refer to those typically provided to all inpatients. Examples of such services include regular room services, minor medical and surgical supplies, and the use of equipment and facilities. See https://grants.nih.gov/grants/policy/nihgps/html5/section_19/19.2_definitions.htm.

[7]Since this cost measure was also studied by Dranove et al. (2014), we can also compare the effects of adoption in the modern era to those results reported in that paper for the earlier period.

[8]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.

outcome measure is a proxy for patient quality of care. We use the adverse drug event (ADE) rate among inpatients in a hospital as a quality of care measure. EMRs make it easier for health professionals to access useful information about medications, which could reduce prescribing errors and improve quality of care. ADE rates 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 discharges at 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 use MedPAR data to construct these ADE rates. Due to data limitations, our analyses with this outcome occur over the period 2006-2010.[9]

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 2017.

Prior studies defined EMR capabilities by either enterprise EMR[10] or CPOE (Lee et al., 2013; McCullough et al., 2016; Ganju et al., 2015). We define a hospital to have adopted EMRs if the

[9]Our access to the MedPAR data is limited to 2006-2010.

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

component CPOE has been installed in the hospital in a given year during our period of study.[11] We focus on CPOE because of the variation in its uptake over the period and because of its potential to reduce medical or drug-related errors, which leads to cost savings and improves quality of care. We will consider an alternative definition of EMR adoption, which allows hospitals to install either of the two advanced components, CPOE or PD, as a robustness test. We supplement our HIT data with 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, total admissions, births, system affiliation, organization structure, ownership status, and other characteristics. We match data from the three sources above using a hospital's Medicare provider number.[12] We also supplement our HIT data with demographic data taken from the 2000 US Census for the counties in which hospitals are located (U.S. Census Bureau). Our demographic characteristics include the county population, 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 start with approximately 4,900 hospitals per year in the HIMSS analytic database. With the data from 2005–2017, there are about 63,000 observations in total. We then remove hospitals that were dealing with multiple during the sample period, and the total number drops to 50,664.[13] 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 43,906 observations or about 3,500 hospitals. We merge the

[11] 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.

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

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

health IT data with the hospital cost reports, with over 97% of hospitals matched for the outcome measures—average costs and discharges. We also examine the quality measure—ADE rates using a shorter period, from 2006 to 2010, which leaves us with 16,155 observations or approximately 3,200 hospitals.[14]

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 91.0% in 2017.[15] The increase in adoption during our sample period correlates with an increase in activity to promote HIT during the Bush administration in 2006-2007 and with the subsequent passage of the HITECH Act in 2009.[16] The sharp increase in EMR adoption observed after 2010, however, is likely due to the HITECH Act.[17]

Table 1 presents the summary statistics for the outcome measures, hospital, and demographic characteristics broken down by EMR adoption status. The first column presents the means for the overall sample period 2006-2017, while the second column reports the means among non adopting hospitals (those that never adopt CPOE before or during our sample period). The third column presents the means for adopters, which include all hospitals whose initial adoption of

[14]We lost some hospitals because of missing data when we merge the HIMSS data with the MedPAR data.

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

[16]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. The actions taken by Bush may have fueled hospital expectations of a government incentive program for EMRs even prior to the HITECH Act.

[17]Given the lag time between the contract stage and the live and operational stage, hospitals who contracted with an EMR vendor in 2009 after the HITECH act was passed would be more likely to have their systems be live and operational by 2011.

CPOE took place during the sample period. For the purposes of this table, column 3 includes only pre adoption observations. The average cost of routine inpatient care per discharge over the sample period is $6401. The average cost among adopters in the pre period, $6424 exceeds the average cost of non adopters, $6207. The overall mean for average operating expenses per discharge, a broader measure of costs used in an alternative test, is $52,825 and adopters also have higher operating expenses on average ($55,187) than non adopters ($32,991). The mean number of hospital discharges per year is 6459, with adopters having fewer annual discharges pre adoption (6450) compared to non adopters (6539). The average adverse drug event (ADE) rate is 6.55 over the period 2006-2010, with adopters having a higher mean ADE rate (6.7) compared with non adopters (6.5). The hospital characteristics show that non EMR adopters are hospitals with fewer beds and fewer births on average. They are also located in counties with larger populations and higher percentages of Black and Hispanic residents (over the whole sample period) compared to adopters (in the pre adoption period). However, adopters have more total admissions pre adoption compared to non adopters over the whole sample period. Adopters are also more likely to be non profit hospitals with a higher percentage of Medicare discharges and less likely to be for profit hospitals. To address any level differences between adopters and non adopters, we include hospital fixed effects in our regressions as well as time varying hospital and demographic characteristics.

5 Empirical Strategy

5.1 Initial EMR adoption: No vendor heterogeneity

We first estimate the effect of EMR adoption on hospital outcomes using a difference in differences model that exploits variation in the timing of adoption. Our model compares outcomes for hospitals who adopt EMRs (in 2006 to 2017) and hospitals who do not adopt EMRs (never or non adopters). We focus on a hospital's initial adoption decision to better identify the effect of the health information technology on hospital performance.[18] This case provides a benchmark for assessing EMR performance.

We estimate the following regression

$$Y_{it} = \beta \text{EMR}_{it} + \alpha_i + \gamma_{st} + \mu \text{adopter}_i \times t + \delta X_{it} + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the outcome variable for hospital i in year t. The variable $\text{EMR}_{it} = 1$ if hospital i adopted CPOE in year t or an earlier year.[19] 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-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. The variable $\text{adopter}_i = 1$ if hospital i adopted an EMR by the end of the sample period. It indicates whether a hospital is an *ever* adopter and remains constant during the entire sample. We interact this variable with t, which denotes year t to capture an adopter-

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

[19] Results using an alternative measure of adoption, the installation of either advanced component, CPOE or PD, are reported in the appendix.

specific time trend. Including a differential trend based on the hospital's eventual adoption status allows for different types of hospitals to experience different trends as in Agha (2014). X_{it} is a vector of hospital and demographic characteristics of hospital i at time t. Hospital 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, whether a hospital 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, 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.[20] The demographic characteristics include the following variables: 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.[21] Local demographics are likely to be a good predictor of hospital patient flows (Billings et al., 1993; Laditka et al., 2003) and may also influence the cost of care. We interact the value of these characteristics in the base year 2000 with a linear time trend to allow for time-variation in local environments in which a hospital operates.

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 may lower average hospital costs, increase patient volume, or reduce adverse drug reaction rates. Each unit of observation is the average

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

[21]We merge our datasets with US census data and extract the demographic variables from the 2000 US Census. We then link these variables with each hospital by county.

across all in-sample patients discharged from that hospital in a particular year. Accordingly, we weight observations by the average total discharges at the hospital level across the years of our sample. We cluster our standard errors at the hospital level.

We also estimate a second regression in which we decompose the effects of EMRs by time since adoption as in Dranove et al. (2014).

$$Y_{it} = \beta_1 \text{EMR}_{it} + \beta_2 \text{EMR}_{it-3} + \alpha_i + \gamma_{st} + \mu \text{adopter}_i \times t + \delta X_{it} + \varepsilon_{it}, \tag{2}$$

Following Dranove et al. (2014), our specification splits the EMR term into two pieces based on years since adoption. The first EMR_{it} term is equal to 1 in the year of adoption and the first two years after EMR adoption. The second EMR_{it-3} term is equal to 1 for hospitals who adopted at least 3 years ago. Hence, the coefficients β_1 and β_2 will reveal the extent to which the effects of EMRs vary over time or differ by a hospital's years of experience with an EMR system.[22]

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

[22] Dranove et al. (2014) who studied the effects of EMR adoption between 1996 and 2009 found that the effects of EMRs varied by time since adoption and by location.

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 from the control prior to and after EMR adoption (Autor, 2003).

Figure 2 shows that coefficients for the treatment group trend prior to EMR adoption are not significantly different than zero for average inpatient costs, the logged number of total hospital discharges, and ADE rates. 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 2.[23]

5.3 Vendor-specific effects

A third specification allows for vendor heterogeneity and examines the extent to which the adoption of different EMR vendors affects hospital performance. Building upon (1) we estimate:

$$Y_{it} = \sum_{k=1}^{K} \beta_k \text{EMRvendor}_{it}^k + \alpha_i + \gamma_{st} + \sum_{k=1}^{K} \mu_k (\text{adopter}_i^k \times t) + \delta X_{it} + \varepsilon_{it} \tag{3}$$

Let k represent a particular vendor from the set of active vendors in the market, $\{1, 2, ..., K\}$. We assume $\text{EMRvendor}_{it}^k = 1$ if vendor k was adopted in hospital i at time t or in an earlier year. We

[23] We report a similar figure, Figure A1, for average operating expenses in the appendix and also find that the coefficients for the treatment group prior to adoption are not significantly different than zero. We can not reject the premise of a common pre trend among treatment and control groups for this measure. These p value for this test is reported in the first column of Table A1.

include 12 major vendors of inpatient EMR systems and group those remaining into a class called "others".[24] These vendor-specific dummy variables will reveal the impact of different vendors' EMR systems on hospital performance by controlling for potential variation among the vendors' EMRs, such as differences in ease of use, customer support/training/system maintenance, and interoperability discussed earlier. As in (1) we control for hospital fixed effects α_i, state-year fixed effects γ_{st}, and a rich set of hospital and demographic characteristics X_{it}. The variable $\text{adopter}_i^k = 1$ if hospital i adopted vendor k's EMR by the end of the sample period. It indicates whether a hospital is an *ever* adopter of a particular vendor and remains constant during the entire sample. We interact this variable with t, which denotes year t to capture a vendor-specific time trend. Including such differential trends based on the hospital's eventual adoption status and vendor allows for different types of hospitals to experience different trends.

$$Y_{it} = \sum_{k=1}^{K} \beta_{1k}\text{EMRvendor}_{it}^k + \sum_{k=1}^{K} \beta_{2k}\text{EMRvendor}_{it-3}^k + \alpha_i + \gamma_{st} + \sum_{k=1}^{K} \mu_k(\text{adopter}_i^k \times t) + \delta X_{it} + \varepsilon_{it} \tag{4}$$

We then estimate a fourth specification that splits the *EMRvendor* term into two pieces based on time since adoption. The first EMRvendor_{it}^k term is equal to 1 in the year of a vendor's adoption and the first two years after adoption. The second $\text{EMRvendor}_{it-3}^k$ term is equal to 1 for hospitals who adopted a vendor's EMR at least 3 years ago. Hence, the coefficients β_{1k} and β_{2k} will reveal the extent to which the effects of a vendor's adoption vary over time or differ by a hospital's years of experience with a vendor's EMR.

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

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. In theory, the endogeneity could arise from two sources. 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 outcomes. Both could lead to differential pre trends and pose a source of bias to OLS estimates. We take an approach that tests for the joint effect of such bias by examining whether each treated group (hospitals who adopt a particular vendor) has a differential pre trend compared to our control group, non adopters.[25] We believe that this approach will yield similar insights about the extent to which endogeniety poses a threat to our estimation strategy. We estimate a regression similar to (3) that includes terms for each treated group (adopter of vendor k) and then interact those treatment variables with a set of dummy variables for each year t prior to and after a hospital's adoption decision. We then test for whether the coefficients for each vendor's yearly interaction terms are jointly zero in the years prior to adoption (Autor, 2003). This will produce a series of pre trends tests, one for each vendor. If the coefficients on these yearly interaction terms are jointly zero for any given vendor, then we can not reject the premise of a common pre trend among treated (hospital adopting that vendor) and control groups (non

[25] Although we can not separate the bias arising from the timing of adoption and the choice of vendor, our test will reveal whether the joint effect of these factors produces differential pre trends by vendor. This is similar to the approach used to examine pre trends in prior studies that did not account for vendor heterogeneity.

adopters).

Table 2 presents a summary of the results from these tests in column 2. For the average inpatient cost outcome, 12 out of 13 vendors pass the pre trends test. For total hospital discharges, 11 out of 13 vendors pass the pre trends test, while for ADE rate, 10 out of 13 pass the pre trends test.[26] The results provide little evidence of differential pre trends by vendor compared to the control group (non adopters) for our outcome measures. This evidence suggests that any bias arising from the timing of adoption and choice of vendor does not threaten the validity of our research design.

Although we do not find evidence of bias arising from differential pre trends by vendor, we will also conduct a robustness test which uses an instrumental variable (IV) approach to further examine the potential for endogeneity due to selection bias. More detail on the IV analyses and results will be presented in the robustness section.

6 Results

6.1 No vendor heterogeneity

The regression results without vendor heterogeneity for our three outcome measures are presented in Table 3. For simplicity we report the coefficient of adopt, β, which represents the marginal effects of EMR adoption on each outcome, in the first row. We report the coefficients of $adopt < 3\ years$ and $adopt \geq 3\ years$, β_1 and β_2, which represent the marginal effects of EMRs in the first two years after adoption and the marginal effects of EMRs three or more years after adoption, in

[26] We report the pre trends results for our alternative cost measure, average operating expenses, in the appendix in the second column of Table A1. Eleven of the 13 vendors pass the pre trends tests.

the second and third rows, respectively.

Results in columns 1 and 3 show that on average EMR adoption over the period from 2006-2017 has no significant impact on average inpatient costs and logged inpatient discharges. Agha (2014) who focused on the effects of adoption in an earlier period (1998-2005) prior to HITECH also found no evidence that EMR adoption reduced medical expenditures among Medicare patients. Results in column 5 show that EMR adoption has no significant impact on the rate of adverse drug events on average, a result that differs from Agha (2014) who finds a positive effect of EMR adoption on ADE rates in 1998-2005.[27]

The second and third rows of Table 3 present the effects based on time since EMR adoption. The results on the second row show that there is no significant impact of EMR adoption on outcomes in the first two years after adoption. None of the coefficients in row 2 are significantly different than zero for average inpatient costs, logged inpatient discharges, and ADE rates. There are also no significant effects of EMR adoption for hospitals who adopted EMRs at least 3 years ago on average inpatient costs and ADE rates. However, we do observe that hospitals who adopted EMRs at least 3 years ago experience an increase in the volume of inpatient discharges. The coefficient in column 4 for logged inpatient discharges is positive and significant for hospitals who adopted EMRs at least three years earlier, which suggests that some effects of EMRs may only emerge after hospitals gain experience with the EMR.

The results without vendor heterogeneity suggest that the adoption of EMRs produced limited benefits for hospitals. On average, there is no evidence of cost savings (for routine inpatient care) or

[27] Freedman et al. (2018) who studies a different patient population, younger non-Medicare patients, and adoption decisions in 2003-2010 observes a negative effect of EMR adoption on the ADE rates for patients with less complex conditions.

improved safety outcomes (for ADE rates) following EMR adoption.[28] There is some evidence that hospitals who have at least three years experience with EMRs see an increase in inpatient volume. Next, we allow for vendor heterogeneity and examine the extent to which there are heterogeneous effects of adoption vary by vendor.

6.2 Vendor-specific effects

Table 4 presents the results (with vendor heterogeneity) for average inpatient costs per discharge. Column 1 presents the overall effect of the vendor's EMR on the outcome, while columns 2 and 3 present the effects by time of adoption: first two years after adoption in column 2 and three or more years after adoption in column 3. Each row shows β_k for a particular vendor, which represents the marginal effects of EMR adoption of vendor k on the outcome. The bottom of each column reports the p values associated with the tests for joint insignificance and joint equality of the vendor-specific coefficients. These tests will reveal the extent to which (i) the vendor-specific effects matter (or are jointly different than zero) and (ii) the extent to which those vendor-specific effects differ (meaning that we can reject that they are equal).

Table 4 shows that the impact of EMR adoption on average inpatient costs varies by vendor and varies by time since adoption. Focusing on the overall results with vendor heterogeneity, in column 1 we see positive coefficients for the adopters of two EMRs vendors, which indicates overall cost increases (ranging from 5.3% to 6.6%) for adopting hospitals. For the remaining vendors, we see

[28] Using our alternative cost measure, we also find that EMR adoption has no overall or immediate impact on average operational expenses following adoption. Unlike Table 3, however, Appendix Table A2 shows there is a negative and significant effect of adoption on average operational expenses three or more years after adoption. This is similar to results reported in Dranove et al. (2014) who examined the effects of EMR adoption in the pre HITECH era, 1996-2010.

no significant effects of EMR adoption on average inpatient costs. Focusing on the effects in the first two years after adoption, in column 2 we see a negative coefficient for the adopters of one EMR vendor, which suggests costs savings (6.1%) in hospitals who adopt that vendor. We also see positive coefficients for the adopters of two EMRs vendors, which indicates cost increases (ranging from 4.9% to 5.9%) for adopting hospitals. For the remaining vendors, we see no significant effects of EMR adoption on average inpatient costs in the first two years after adoption. Considering the effects three or more years after a vendor's adoption, in column 3 we see more evidence of cost savings, but only for a few vendors. There are negative coefficients for the adopters of three EMR vendors, which suggests a reduction in average inpatient costs (ranging from 2.7% to 14.3%) in hospitals who adopt those vendors. We also continue to see positive coefficients for the adopters of two EMRs vendors, which indicates that those adopting hospitals experienced increased costs even after 3 years of experience with the vendor. For the remaining vendors, we see no significant effects of EMR adoption on average costs per discharge three or more years after a vendor's adoption. The p-values at the bottom of each column indicate that we can reject that the vendor effects are jointly zero and jointly equal. These tests provide evidence that there are heterogeneous effects of EMR adoption by vendor and by time since adoption on average inpatient costs.[29]

The first panel of Figure 3 provides a visual illustration of this heterogeneity. Figure 3 depicts the effects by vendor on average inpatient costs from column 3 in Table 4. The figure shows that only some vendors deliver on the eventual promise of cost savings, while the adoption of other vendors' EMRs lead to either increased costs or no change in average inpatient costs. Hospitals will face different cost implications depending on the vendor adopted.

[29]We do not find heterogeneous effects by vendor of EMR adoption on average operational expenses. In Table A3 the p-values show that we can not reject that the vendor effects are jointly zero and jointly equal.

Table 5 shows that the impact of EMR adoption on inpatient discharges also varies by vendor, but those effects only materialize after three or more years following adoption. The p-values at the bottom of each column indicate that we can reject that the vendor effects are jointly zero and jointly equal only in column 3. We can not reject that the coefficients are jointly zero and jointly equal in columns 1 and that the coefficients are jointly zero in column 2. In column 3, hospitals who adopted four EMR vendors had increases in inpatient volume after three years, while hospitals who adopted two other EMR vendors saw reductions in inpatient volume after three years, and hospitals who adopted the remaining vendors saw no change in inpatient volume. These results provide additional evidence of heterogeneous effects and suggest that effects of EMR adoption on the volume of inpatients depend on the vendor and the time since adoption.

The second panel of Figure 3 provides a visual illustration of this heterogeneity. It depicts the effects by vendor on logged inpatient discharges from column 3 in Table 5. The figure shows that only some vendors deliver increased inpatient volume three years after adoption, while the adoption of other EMR vendors lead to either reduced inpatients or have no significant effect.

Table 6 shows that there are heterogeneous effects of EMR adoption on ADE rates by vendor. The p-values at the bottom of each column indicate that we can reject that the vendor effects are jointly insignificant, and reject that they are jointly equal. In column 1, 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.[30] This represents an improvement in 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

[30] 10.2% = 0.67 / 6.55 and 25.9% = 1.7 / 6.55, where 6.55 is the average ADE rate across the five years.

points, and no significant effects for the adopters of remaining vendors. Results in column 2 show that EMR adoption reduced ADE rates for the same four vendors in the first two years after adoption. The effects range from .7 to 1.7 percentage points (10.7% to 25.9% of the mean ADE rate).[31] We see an increase in the ADE rate for the adopters of one vendor, similar to that observed in column 1. In column 3, the EMRs from two vendors lead to reductions in ADE rates three or more years after adoption, which range from 1.8 to 2.7 percentage points (27.5% to 41.2% of the mean ADE rate).[32] Hospitals who adopted one vendor continue to see increases in ADE rates three or more years after adoption. There are no significant effects of EMR adoption on ADE rates observed for remaining vendors three or more years after adoption.[33] These results suggest that the differences among vendors matter for explaining changes in ADE rates and these effects arise shortly after adoption. The third panel of Figure 3 provides a visual illustration of this heterogeneity. It depicts the effects by vendor on ADE rates from column 1 in Table 6. The figure shows that several vendors, but not all, deliver increased quality of care (measured by ADE rates) following EMR adoption.

To further illustrate the effects of EMR adoption on cost savings versus inpatient volume, we construct Figure 4, which plots the vendor-specific coefficients from the regression for average inpatient costs (from Table 4, column 3) against the coefficients from the regression for logged inpatient discharges (from Table 5, column 3). While only suggestive, this figure shows how the various results for different vendors may fit together. For instance, Figure 4 shows that several vendors are able to deliver both cost savings and improved inpatient volume at the same time.

[31] 10.7% = 0.7 / 6.55 and 25.9% = 1.7 / 6.55.

[32] 27.5% = 1.8 / 6.55 and 41.2% = 2.7 / 6.55.

[33] The effects for three or more years after adoption have slightly larger standard errors than in columns 1 and 2 perhaps because there are fewer hospitals with 3 or more years of experience by the end of the sample period, 2010.

These vendors are located in the top left quadrant of Figure 4. However, there are other vendors whose adoption leads to increased average costs and fewer inpatient discharges as shown in the bottom right quadrant. This suggests an inverse relationship between changes in inpatient costs and changes in inpatient volume. Hospitals who experience cost savings in routine inpatient care also experience a higher volume of inpatients, while hospitals who experience cost increases in routine inpatient care see a reduction in inpatients.

To illustrate the effects of EMR adoption on cost savings versus care quality, we construct Figure 5, which plots the vendor-specific coefficients from the regression for average inpatient costs (from Table 4, column 3) against the coefficients from the regression for the ADE rate (from Table 6, column 1). While only suggestive, this figure shows the extent to which a vendor's adoption presents trade-offs between the goals of cost savings and improving care quality. Figure 5 shows that only some vendors (in the bottom left quadrant) are able to deliver both cost savings and improved quality of care at the same time. For other vendors achieving improvements in care quality (in the form of reduced ADEs) requires increased costs as shown in the bottom right quadrant. This reflects more of a pattern of substitution for these vendors.[34]

Finally to illustrate how the adoption of different EMR vendors affects volume of inpatients versus quality of care, Figure 6 plots the vendor-specific coefficients from the regression for the number of inpatient discharges from Table 5 (column 3) against the coefficients from the regression for the ADE rate from Table 6 (column 1). While only suggestive, this figure shows the extent

[34]Two vendors are associated with reduced care quality and increased costs. However, one vendor who is located in the upper right quadrant does not have significant coefficients from either costs or ADE regressions, while the other vendor only has a significantly positive coefficient in the costs regression, but does not have a significant coefficient in the ADE regression. There is only one vendor in the upper left quadrant who experiences cost savings from adoption, and a reduction in care quality.

to which a vendor's adoption presents trade-offs between care quality and patient volume. Figure 6 shows that there are several vendors for which the adoption of EMRs resulted in both increased patient volume and improvements in care quality. The bottom right quadrant depicts the vendors who were able to deliver both more inpatients and reduced ADE rates. However, as in Figure 5, not all vendors deliver gains in both areas. The bottom left quadrant depicts the vendors whose products led to reduced ADEs, but fewer inpatient discharges. For these adopting hospitals, the vendor's EMR technology was able to deliver improved patient quality, but only with lower inpatient volume. The results shown in Figures 5 and 6 suggest that different vendors' EMRs present different trade offs to adopting hospitals.

6.3 Robustness Tests

We first examine the sensitivity of our results to an alternative definition of EMR adoption, which allows for the use of different advanced components. For these tests, we define EMR adoption as a hospital who has installed either 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 of the adoption of advanced EMR components more generally. Figure A2 shows that the proportion of hospitals who adopt either advanced component is higher than in Figure 1 so we are able to capture more adopters using this alternative measure. Hospitals who adopted EMRs (defined as either CPOE or PD) increased from 5.9% in 2006 to 94.8% in 2017. 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, the three panels in Figures A3 show that there are no significant pre trends (for the treated group) among the outcome variables using 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, which are reported in the first column of Table A4, show that we can not reject the premise of common pre trends (at the 95% confidence level) among treatment and control groups under our alternative adoption definition.[35] We next allow for vendor heterogeneity and examine the pre trends by vendor. The results are summarized in column 2 of Table A4 by outcome. Ten out of 13 vendors pass the pre trends test for average inpatient costs. Seven out of 13 vendors pass the pre trends test for the ADE rate, smaller than for our primary adoption definition. Nine out of 13 vendors that pass the pre trends test for logged inpatient discharges. Our tests provide evidence of no differential pre trends by vendor compared to the control group (non adopters) for average costs and discharges, but more limited evidence for the ADE rate outcome using the alternative definition of adoption.

Table A5 shows that the results (without vendor heterogeneity) using our alternative measure of EMR adoption are similar to those previously reported in Table 3 for our primary outcomes.[36] There are no significant effects of EMR adoption on most outcomes using the alternative adoption definition. As in Table 3 we observe that hospitals who adopted EMRs at least 3 years ago experience an increase in inpatient volume. The coefficient in the third row, column 4 for logged inpatient discharges is positive and significant as in Table 3. This supports our finding that some

[35]The p-value for discharges is weakly significant at the .1 level, but Figure A3 shows little evidence of any trend.

[36]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.

effects of EMRs may only emerge after hospitals gain experience with the EMR.

Table A7 presents the results of EMR adoption on average inpatient costs with vendor heterogeneity using the alternative adoption definition. The signs of most coefficients are similar to those reported in Table 4, but there are fewer significant coefficients in each column. We continue to see that the coefficient for HMS is positive and significant coefficient in all columns, which indicates overall cost increases for adopting hospitals as in Table 4. The coefficient for Healthland while positive is not significant in any column as it was in Table 4. In columns 2 and 3, the coefficients for GE have the same sign as in Table 4, but are not significant in Table A7. Although the coefficients for Meditech, QuadraMed are negative as in Table 4, they are not significant in column 3 in Table A7. The coefficient for Other (EMR vendors) has a negative coefficient in both tables in column 3, but is only significant in Table A7. Also, unlike Table 4, we can only reject that the vendor effects are jointly zero and jointly equal in column (3), 3 or more years after adoption. Hence, heterogeneous effects by vendor on inpatient costs emerge only 3 or more years after adoption using our alternative adoption definition. The first panel of Figure A4 provides a visual illustration of this heterogeneity using the estimates from column 3 in Table A7.

Table A8 presents the results of EMR adoption on the number of inpatient discharges with vendor heterogeneity using the alternative adoption definition. Focusing on column 3, the signs and significance of the coefficients are mostly similar to those reported in Table 5, which suggests similar patterns of heterogeneous effects of adoption by vendor on inpatient discharges three or more years after adoption. Hospitals who adopted Epic, GE, Meditec, Other vendors had increases in inpatient volume, while hospitals who used CPSI saw reductions in inpatient volume after adoption. These results show that our key findings from Table 5 about the effects of vendor adoption on

inpatient volume three or more years after adoption are not sensitive to our definition of adoption.[37]

Table A9 presents the results of EMR adoption on the ADE rate with vendor heterogeneity using the alternative adoption definition. As in Table 6 there is a pattern of heterogeneous effects of adoption (by vendor) on ADE rates. The p values at the bottom of the columns in Table A9 indicate that we can reject that the vendor effects are jointly zero and jointly equal in all time periods after adoption. Focusing on the overall results in column 1, hospitals who adopted Eclipsys, GE, QuadraMed, Other vendors had reductions in the ADE rate that ranged from .61 to 2.06 percentage points similar to Table 6. The coefficient for Meditech although positive in both tables was no longer significant in Table A9. The coefficients for Cerner and Siemens although insignificant in Table 6 were positive and significant in Table A9, which suggests increases in the ADE rates for hospitals who adopted those vendors.

In a second robustness test, we examine whether our results are sensitive to the staggered effects of EMR adoption over time. Recent literature raised concerns about the potential bias in the estimates from the two-way fixed effects regression when the treatment timing varies across units and the treatment effects are different within-unit over time or between groups that get treated at different periods (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). In our setting, hospitals adopt EMRs in different years during the sample period, leading to staggered treatment timing. To examine whether the effects of general EMR adoption results from the two-way fixed effects estimator are subject to such bias, we re-estimate the main specification in (1) for each outcome following De Chaisemartin and d'Haultfoeuille (2020) and De Chaisemartin and D'Haultfoeuille (2022). The general idea is

[37]There is more support for heterogeneous vendor effects in all time periods (see p values at the bottom of each column) using the alternative adoption definition than in Table 5.

to compare the $t-1$ to t outcome evolution of hospitals going from no EMRs to having EMRs from $t-1$ to t, and of hospitals that remain with no EMRs at both periods. Table A6 presents the results from this estimation. As in Table 3, we can not reject the premise of common pre trends among adopters and non adopters after adjusting for staggered adoption effects.[38] Our results for the effects of adoption on average inpatient costs and discharges are not sensitive to the adjustment for staggered effects. In Table A6 as in Table 3, the coefficients for adopt are not significantly different than zero for these outcomes. Unlike Table 3 we do observe a small positive yet significant coefficient for the effects of adoption on ADE rates in Table A6, which suggests that the results for ADE rates may be somewhat sensitive to the adjustment for staggered adoption.

Investigating the issue of staggered adoption effects by vendor is somewhat problematic. The reason is that with the De Chaisemartin and d'Haultfoeuille (2020) approach, observations with unbalanced panels (i.e. hospitals that do not have observations in all years of the sample) will be dropped from the analysis. Hence, estimates of the staggered adoption effects by vendor may be based on relatively few observations especially if the hospitals adopting that vendor are not observed in all years in the sample. Hence, the staggered adoption effects by vendor analysis leads to biased estimates for some vendors due to small sample bias.

Instead, we will investigate possible endogeneity due to vendor selection in a third robustness test. Although we find little evidence of differential pre trends by vendor in our outcomes among adopters and non adopters, there are still 1-3 vendors which fail the pre trends test for each outcome as shown in Table 2. Such failures may suggest that there are unobservables that might

[38] The p values for our tests of joint significance of the pre period coefficients (for each outcome) are reported in the bottom row of Table A6.

impact vendor selection and also influence hospital outcomes.[39] To investigate the sensitivity of our results to potential endogeneity bias arising from vendor selection, we conduct an instrumental variable analyses using a two-stage residual inclusion approach. The analysis exploits variation in the timing of vendor adoption by hospitals as predicted by our instruments to remove any possible selection bias. In the first stage, we use a multinomial conditional logit model to estimate a hospital's vendor adoption choice as a function of instruments that we believe are correlated with a hospital's vendor choice, but unrelated to the unobservables expected to influence hospital outcomes. Given the nonlinear estimation in the first stage, we then use a two stage residual inclusion method as in (Terza et al., 2008; Desai, 2016; Holmgren et al., 2017) to estimate hospital outcomes. Under this method, we include the residuals from the first stage estimation (for each vendor) as regressors in the second stage estimation of (3).

We rely on an instrument that is correlated with a hospital's decision to adopt an EMR vendor, but otherwise uncorrelated with our hospital outcomes. The instrument is a measure of vendors adopted by hospitals that are within a geographic proximity to a target hospital as in Holmgren et al. (2017). Our instrument is defined as the proportion of hospitals who are using a particular vendor within a 30-60 mile radius of the target hospital.[40] Our 30-60 mile radius captures regional variations in EMR vendor marketing, which are likely to influence hospital vendor choice, but does not include hospitals who directly compete for patients with the target hospital.[41] Our identifying assumption is that our instrument accounts for variation in the EMR adoption and vendor decisions,

[39] Examples of such factors may be a hospital's management quality, its organizational culture, or its resources (Holmgren et al., 2017).

[40] Holmgren et al. (2017) uses vendor market shares in a 15-50 mile radius of the target hospital. However, when we adopted this radius, we find that the instrument is still correlated with our outcomes. To remedy this, we choose a radius that is slightly farther away from the hospital, 30-60 miles, to avoid such correlation.

[41] Such competing hospitals may have a differential effect on vendor choice.

but is unrelated to the unobserved factors that may lead our outcome measure to trend differently for hospitals who adopt a particular vendor relative to hospitals who do not adopt EMRs. Hence the instrument is expected to affect the decision to adopt a vendor, but is not otherwise expected to affect our hospital outcomes. Our tests support this assumption.[42] In addition, our first stage multinomial conditional logit results for the IV analysis reported in Table A10 show that our instruments are strong predictors of EMR vendor adoption.[43]

Table A11, which presents the second stage regression results, shows that the impact of EMR adoption on average inpatient costs varies by vendor and varies by time since adoption similar to the non IV results. The p-values at the bottom of each column in Table A11 indicate that we can reject that the vendor effects are jointly zero and jointly equal at conventional significance levels as in Table 4. The signs of the coefficients are mostly similar to those reported in Table 4, but there are some changes in significance among the vendors in the IV analysis. As in Table 4, results in Table A11 show that the adoption of Healthland leads to cost increases for adopting hospitals in all columns; while the adoption of GE and Meditech lead to costs savings for adopting hospitals three or more years after the adoption. The coefficient for EPIC while negative in both tables becomes significant in all columns in the IV analysis, which suggests that adopting hospitals will see cost savings. The coefficient for Cerner while positive in both tables becomes significant in all columns in the IV analysis, which suggests that adopting hospitals will see cost increases.

Table A12, which presents the second stage regression results, shows the impact of a vendor's

[42]Our tests show that we can't reject the joint insignificance of the instrument when included in each second stage estimation. The corresponding p values for this test in each second stage estimation are p=.53 (average costs); p=.18 (logged discharges); and p=.38 (ADE rates).

[43]The value of the first stage F statistic to test for the significance of the excluded instruments is equal to 175 for vendor choices in 2006-2017 and 42 for vendor choices in 2006-2010.

adoption on logged inpatient discharges. In the non IV analysis in Table 5, we could only reject that the vendor effects were jointly zero and that the vendor effects were jointly equal in column 3, three or more years after a vendor's adoption.[44] Focusing on those results, the signs of the significant coefficients are mostly similar to those reported in Table 5 with some changes in significance and magnitude of the coefficients in the IV analysis. As in Table 5, results in Table A12 show that the adoption of Meditech leads to increases in inpatient volume three or more years after adoption, while the adoption of CPSI and Eclipsys lead to reduced inpatient volume three or more years after adoption, similar to the non IV results. The coefficient for McKessons while positive in both tables becomes significant in the IV analysis, which suggests that adopting hospitals will see increases in inpatient volume. The coefficient for HMS while negative in both tables becomes significant in the IV analysis, which suggests that adopting hospitals will see reduced inpatient volume. The coefficients for EPIC and GE while significant in Table 5, are not significantly different than zero in the IV analysis.

Table A13, which presents the second stage regression results, shows that the impact of EMR adoption on ADE rates varies by vendor and by time since adoption similar to the non IV results. The p-values at the bottom of each column in Table A13 indicate that we can reject that the vendor effects are jointly zero and jointly equal as in Table 6. The signs of the significant coefficients in Table 6 are mostly similar to those in Table A13. However, some coefficients become insignificant or differ in magnitude in the IV analysis, while others increase in significance.[45] Similar to Table 6, Table A13 shows that the adoption of QuadraMed leads to reduced ADE rates for adopting

[44]The p-values at the bottom of each column in Table A12 indicate that we can reject that the vendor effects are jointly zero and jointly equal in all columns.

[45]It is possible that the shorter time frame for the IV estimation of ADE rates, 2006-2010, may contribute to more variability between the IV and non-IV results.

hospitals; while the adoption of Meditech leads to increases in ADE rates for adopting hospitals in the IV analysis. The coefficients for Healthland and EPIC while insignificant in Table 6 become significant in all columns in the IV analysis, which suggests that adopting hospitals will see reduced ADE rates. The coefficients for McKessons and Siemens while positive in both tables becomes significant in all columns in the IV analysis, which suggests that adopting hospitals will see increased ADE rates. The coefficients for Eclipsis and GE become insignificant in the IV analysis.

6.4 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 average inpatient 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 three or more years after adoption as shown in Table 4 column 3—between 2.70% and 14%. On average, the total cost of routine hospital care based on the hospitals in our sample is $228 billion. If all these hospitals were to adopt vendors that lower the cost of routine hospital care after three or more years, the potential annual savings range from $6.16 billion to $31.9 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 $12.8 billion to $66.5 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 ($1,851). 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.[46]

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 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.[47]

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 EMRs 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 show that vendor heterogeneity matters for assessing the effects of EMR adoption on hospital performance. Without vendor heterogeneity, we find no evidence of cost savings or

[46]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.

[47]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).

changes in the care quality arising from EMR adoption. We do find evidence that inpatient discharges increase for hospitals who adopted EMRs at least 3 years earlier, which indicates that time since adoption matters for some outcomes.

With vendor heterogeneity, results show after 3 years of use, there were reductions in the average cost of providing inpatient care in hospitals who adopted three vendors (ranging from 2.7% to 14.3%), increases in inpatient costs for hospitals who adopted two vendors (ranging from 10.1% to 11.1%), and no significant effects for hospitals who adopted other vendors. We also observe increases in inpatient discharges for hospitals who adopted EMRs at least three year ago for four vendors (ranging from 3.3% to 20.3%), decreases in the number of discharges for one vendor (3.3%), and no significant effects for remaining vendors. For patient outcomes, we 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) from the time of adoption between 0.67% and 1.7% for the users of four vendors, increases the ADE rate for the users of one vendor by 0.3%, and has no significant effects for the adopters of other vendors.[48]

Overall, our analyses shows that few vendors deliver cost savings, increased patient volume, and improved care quality at the same time for adopting hospitals. Instead, some vendors who achieve improvements in care quality have increased inpatient costs, a pattern reflecting substitution. In addition, only some vendors who deliver improved care quality do so with higher inpatient

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

volume. For other vendors, improvements in care quality only came with a reduction in inpatients. These results show that there are trade offs to hospitals of adopting different EMR vendors.

Our analyses 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, increased inpatients, and quality of care improvements only arise for the users of some vendors. Our estimates suggest that if all the in-sample hospitals were to adopt the vendors that lower average hospital costs, they could achieve annual savings that range from $6.16 billion to $31.9 billion. The annual savings could range between $12.8 billion and $66.5 billion when extrapolating to the national sample. If all in-sample hospitals adopt EMR vendors who lower the ADR rate, our estimates suggest annual direct savings that range from $8.9 million to $22.3 million, and $32.2 million to $80.4 million per year 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, such bias may be minimal given that 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 their evolution over time impact EMR performance. Future research can better examine these effects. Third, our study only included one quality of care measure, ADE rates, that has 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 vendors' EMRs deliver cost savings, enhanced productivity, and 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. Hospitals who adopt these vendors are not likely to learn about these costs until after substantial investments in HIT are made. To reduce these hidden costs, policymakers could inform providers (ex ante) about the differences in EMR performance by vendor or they could strengthen the requirements for vendor certification and HITECH program participation to help ensure that all certified EMRs deliver the expected efficiencies.

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Table 1: Summary statistics for key variables by adoption status

Variable	All hospitals	Non-adopters	Adopters (pre-adoption)
Financial measures			
Average costs per discharge ($)	6,401	6,207	6,424
Average operational expenses per discharge ($)	52,825	32,991	55,187
Hospital workload			
Total # discharges	6,459	6,539	6,450
Quality measures			
ADE rates (%)	6.55	6.50	6.70
Hospital characteristics			
Staffed beds	165	160	166
Admissions	6,959	6,744	6,984
Births	800	697	812
% of Medicare discharge	49.1	48.4	49.2
% of Medicaid discharge	16.8	17.8	16.7
For-profit hospitals	0.183	0.247	0.176
Not-for-profit hospitals	0.614	0.609	0.615
Equity model hospital	0.015	0.005	0.016
Foundation hospital	0.029	0.028	0.029
Independent practice - - association hospital	0.136	0.155	0.134
Management service - - organization hospital	0.068	0.078	0.067
Residency or Member of - - Council Teaching Hospitals	0.054	0.078	0.051
Affiliated to a hospital system	0.586	0.635	0.580
Critical access hospitals	0.300	0.293	0.301
Demographic characteristics			
Population size	560,230	681,414	546,335
Median household income	38,711	38,690	38,713
Above university degree (%)	9.1	9.5	9.1
Population above 65 (%)	14.0	13.8	14.0
Population between 25 and 64 (%)	60.5	60.6	60.5
% black	10.0	11.4	9.8
% hispanic	9.2	10.6	9.1
# hospitals	3,572	380	3,192

Note: For outcome measures other than ADE rates, table reports the mean values between 2006 and 2017. The mean ADE rates are the average across the years 2006–2010. For hospital characteristics, table reports the mean values in 2006. For demographic characteristics, table reports the mean values in 2000.

Table 2: Summary of pre-adoption trend analysis

	P values on joint insignificance of pre-adoption periods (*adopters* vs. *non-adopters*)	# out of 13 vendors that are NOT significantly different from *non-adopters*
Financial measures		
Average costs per discharge	0.340	12
Quality measures		
ADE rates	0.884	10
Patient Volume		
Total # discharges	0.151	11

Table 3: General adoption effects

	Average costs per discharge		Logged # discharges		ADE rates	
	(1)	(2)	(3)	(4)	(5)	(6)
Adopt	0.000875		0.000727		0.000154	
	(0.00473)		(0.00538)		(0.000837)	
Adopt $<$ 3 years		0.0000302		0.00326		0.000213
		(0.00478)		(0.00539)		(0.000829)
Adopt $\geq$ 3 years		-0.00828		0.0282***		0.00113
		(0.00741)		(0.00851)		(0.00172)
N	42,918		42,928		16,155	

Note: Other regressors include an adopter-specific time trend, hospital fixed effects, state-year fixed effects, and a set of hospital and demographic controls. The hospital controls include the following variables valued 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 was ever a critical access hospital, 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. The demographic controls include the following variables valued in 2000 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 average total discharges at the hospital level (over the years of our sample). Given the shorter time frame for ADE observations, we omit the adopter-specific time trend and the demographic characteristics in ADE estimations in columns (5) and (6). Standard errors clustered at the hospital level and presented in parentheses.

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

Table 4: Vendor-specific effects — financial measure

	Average costs per discharge		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	0.0147	0.0167	0.00209
	(0.0259)	(0.0242)	(0.0352)
Cerner	0.0108	0.0115	0.00338
	(0.00967)	(0.00975)	(0.0140)
CPSI	0.0143	0.0143	-0.0000311
	(0.0190)	(0.0187)	(0.0275)
Healthland	0.0664***	0.0585**	0.151***
	(0.0257)	(0.0239)	(0.0506)
Eclipsys	0.0268	0.0285	0.0658
	(0.0441)	(0.0435)	(0.0581)
Epic	-0.0166	-0.0171	-0.00593
	(0.0111)	(0.0111)	(0.0160)
GE	-0.0526	-0.0612*	-0.143***
	(0.0320)	(0.0317)	(0.0492)
HMS	0.0539**	0.0486**	0.101***
	(0.0227)	(0.0227)	(0.0350)
McKessons	0.00169	-0.00132	-0.00802
	(0.0114)	(0.0114)	(0.0173)
Siemens	0.0210	0.0204	0.0195
	(0.0170)	(0.0169)	(0.0243)
Meditech	-0.00595	-0.00749	-0.0274**
	(0.00829)	(0.00829)	(0.0131)
QuadraMed	-0.0514	-0.0432	-0.142*
	(0.0697)	(0.0664)	(0.0846)
Others	-0.0359	-0.0231	-0.0815
	(0.0312)	(0.0258)	(0.0512)
N		42918	
P-value for joint insignificance	0.0253	0.0297	0.000284
P-value for joint equality	0.0182	0.0201	0.000185

Notes: Other regressors used to estimate average inpatient costs are similar to those used in Table 3 except that we replace adopter-specific time trends with vendor-specific time trends. Clustered standard errors in parentheses.

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

Table 5: Vendor-specific effects — patient volume

	Logged # discharges		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	-0.0520	-0.0734**	0.0455
	(0.0406)	(0.0346)	(0.0522)
Cerner	0.00238	0.00313	0.0103
	(0.0113)	(0.0112)	(0.0181)
CPSI	-0.0648**	-0.0585**	-0.0601*
	(0.0268)	(0.0272)	(0.0320)
Healthland	-0.0337	-0.0277	-0.0629
	(0.0367)	(0.0348)	(0.0753)
Eclipsys	-0.0211	-0.0242	-0.0774**
	(0.0250)	(0.0246)	(0.0368)
Epic	0.0206*	0.0231*	0.0334**
	(0.0121)	(0.0119)	(0.0163)
GE	0.0424	0.0556	0.203**
	(0.0720)	(0.0718)	(0.0979)
HMS	-0.0407	-0.0358	-0.0534
	(0.0266)	(0.0257)	(0.0495)
McKessons	-0.0144	-0.00948	0.0217
	(0.0121)	(0.0122)	(0.0181)
Siemens	-0.00887	-0.00689	0.000718
	(0.0182)	(0.0182)	(0.0254)
Meditech	-0.00302	0.00103	0.0507***
	(0.00955)	(0.00962)	(0.0158)
QuadraMed	-0.0387	-0.0378	0.00991
	(0.0839)	(0.0823)	(0.113)
Others	0.0568	0.0540	0.117**
	(0.0381)	(0.0388)	(0.0461)
N		42928	
P-value for joint insignificance	0.131	0.101	0.000351
P-value for joint equality	0.118	0.0752	0.00218

Notes: Other regressors used to estimate logged inpatients are are similar to those used in Table 3 except that we replace adopter-specific time trends with vendor-specific time trends. Clustered standard errors in parentheses.

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

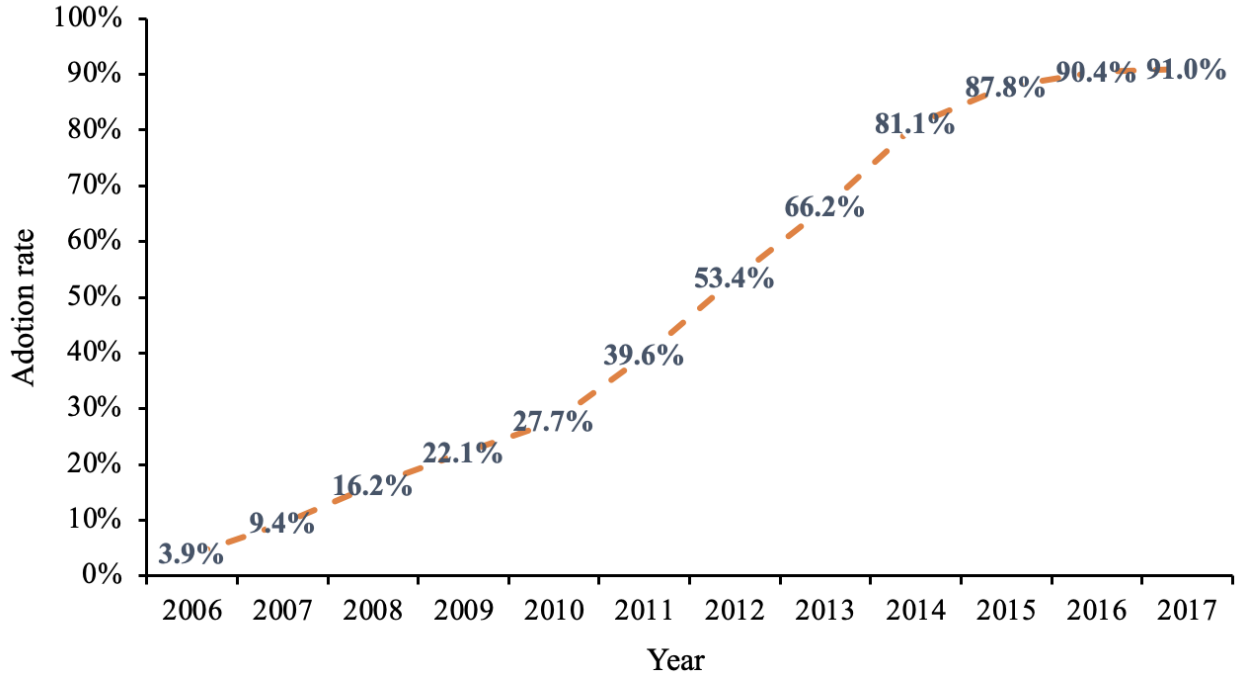
Table 6: Vendor-specific effects — quality measure

	ADE rates		
	Overall (1)	Adoption < 3 years (2)	Adoption ≥ 3 years (3)
Self-developed	-0.0113	-0.0109	–
	(0.00743)	(0.00743)	–
Cerner	-0.00105	-0.00127	0.00181
	(0.00225)	(0.00225)	(0.00395)
CPSI	-0.000725	-0.000502	-0.00254
	(0.00325)	(0.00328)	(0.00650)
Healthland	0.00131	0.00114	0.00945
	(0.00605)	(0.00611)	(0.00678)
Eclipsys	-0.00669**	-0.00695**	-0.00413
	(0.00296)	(0.00304)	(0.00751)
Epic	-0.00185	-0.00161	-0.0105
	(0.00217)	(0.00218)	(0.00655)
GE	-0.0121***	-0.0114***	-0.0180***
	(0.00422)	(0.00416)	(0.00651)
HMS	-0.000855	-0.000579	-0.00354
	(0.00338)	(0.00338)	(0.00671)
McKessons	0.000672	0.000787	-0.000912
	(0.00183)	(0.00185)	(0.00382)
Siemens	0.00348	0.00336	0.00479
	(0.00243)	(0.00239)	(0.00411)
Meditech	0.00301**	0.00296**	0.00662***
	(0.00131)	(0.00131)	(0.00255)
QuadraMed	-0.0167***	-0.0166***	-0.0268***
	(0.00206)	(0.00210)	(0.00835)
Others	-0.0128***	-0.0130***	0.00416
	(0.00471)	(0.00470)	(0.0106)
N		16155	
P-value for joint insignificance	1.95e-14	1.94e-13	0.00118
P-value for joint equality	2.97e-13	1.34e-12	0.00118

Notes: Other regressors used to estimate ADE rates are the same as those used in Table 3. Clustered standard errors in parentheses.

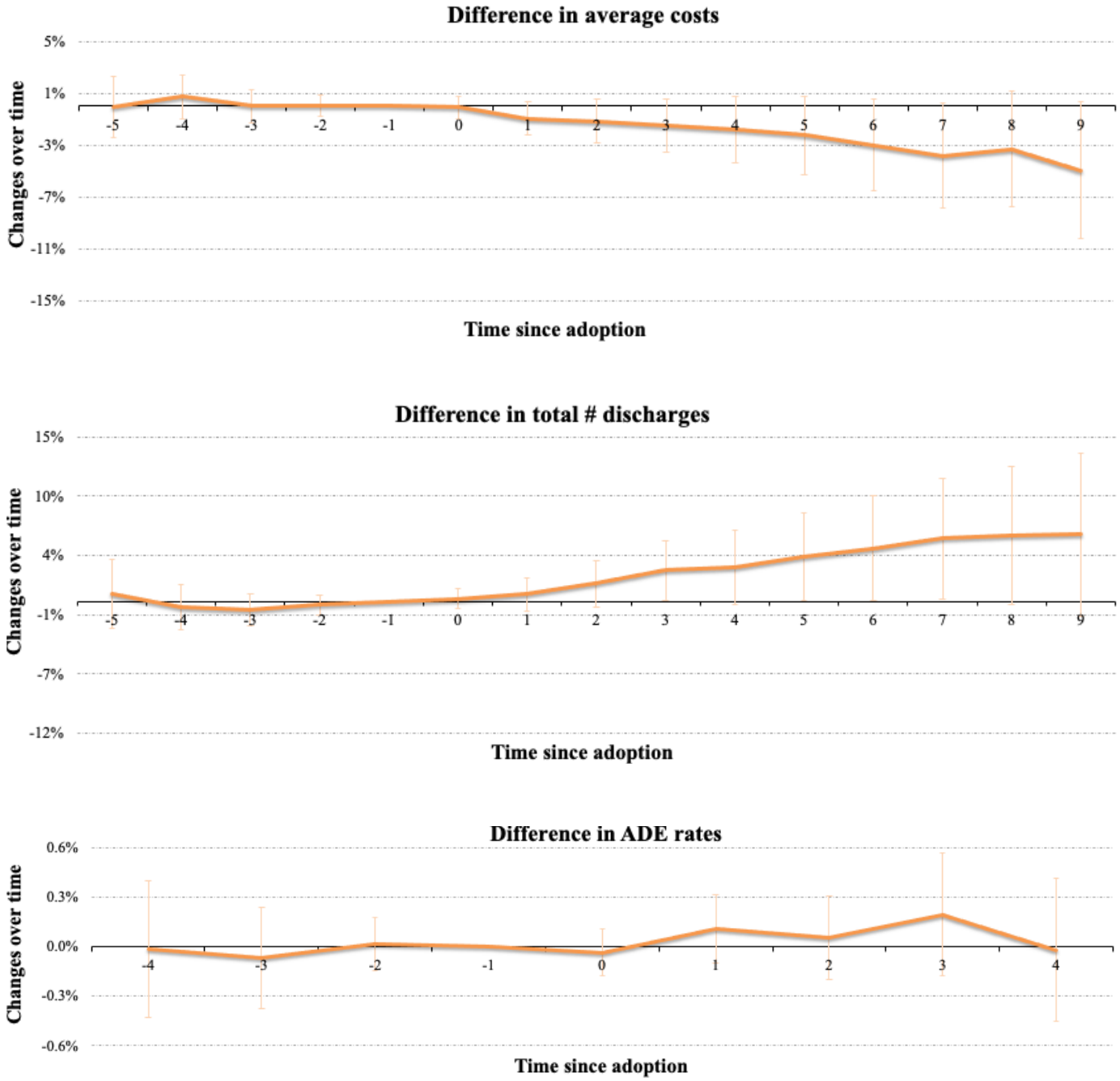
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Adoption rate over time



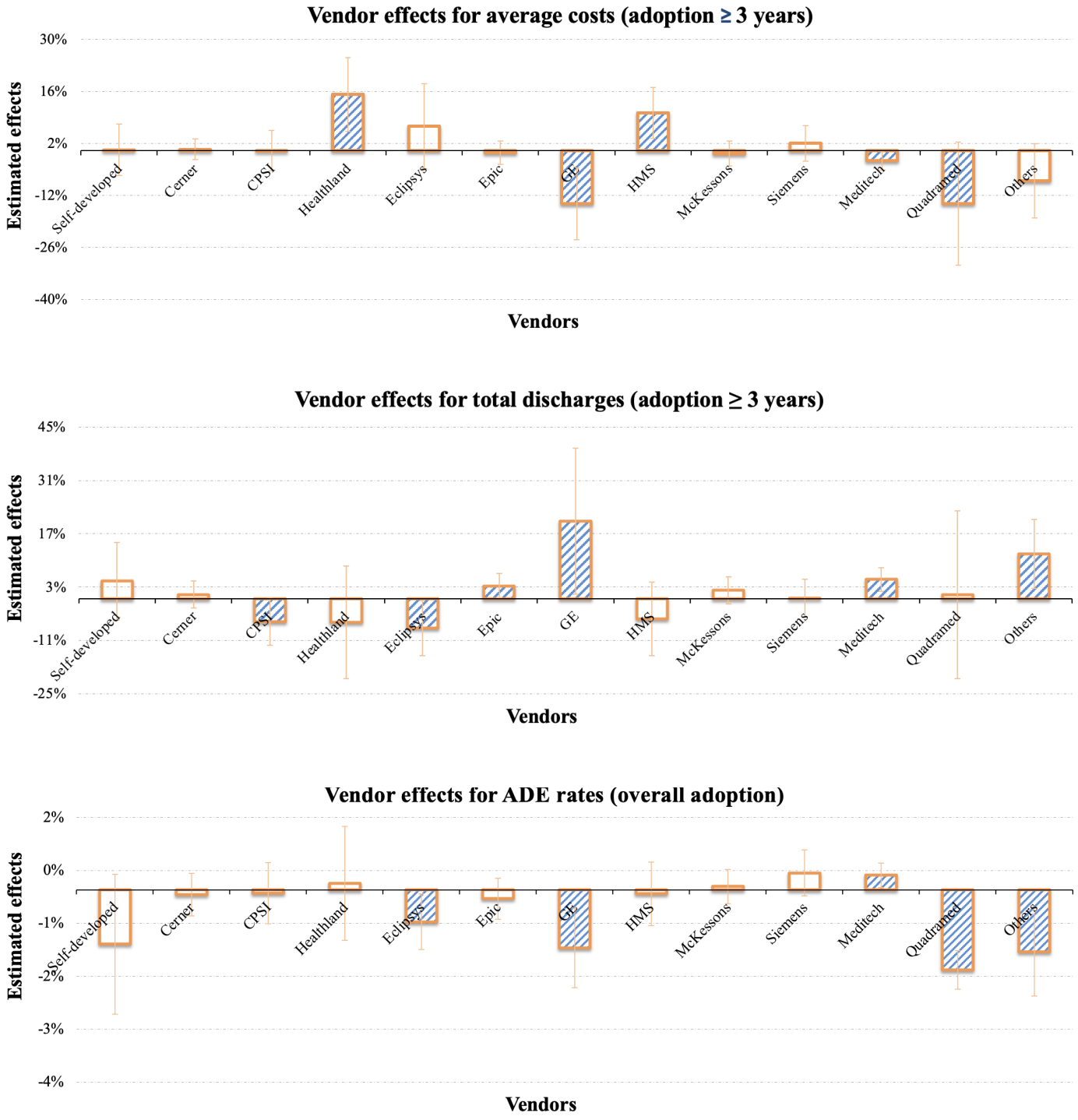
Note: This figure displays the adoption rate of initial adopters of CPOE.

Figure 2: Trends of outcome measures between adopters and non-adopters



Note: Error bars show 95 percent confidence intervals.

Figure 3: Vendor heterogeneous effects by outcome



Note: The shaded bar suggests that the coefficient has at least 10% level of significance. Error bars show 95 percent confidence intervals.

Figure 4: Total # discharges (adoption $\geq$ 3 years) vs. average costs per discharge (adoption $\geq$ 3 years)

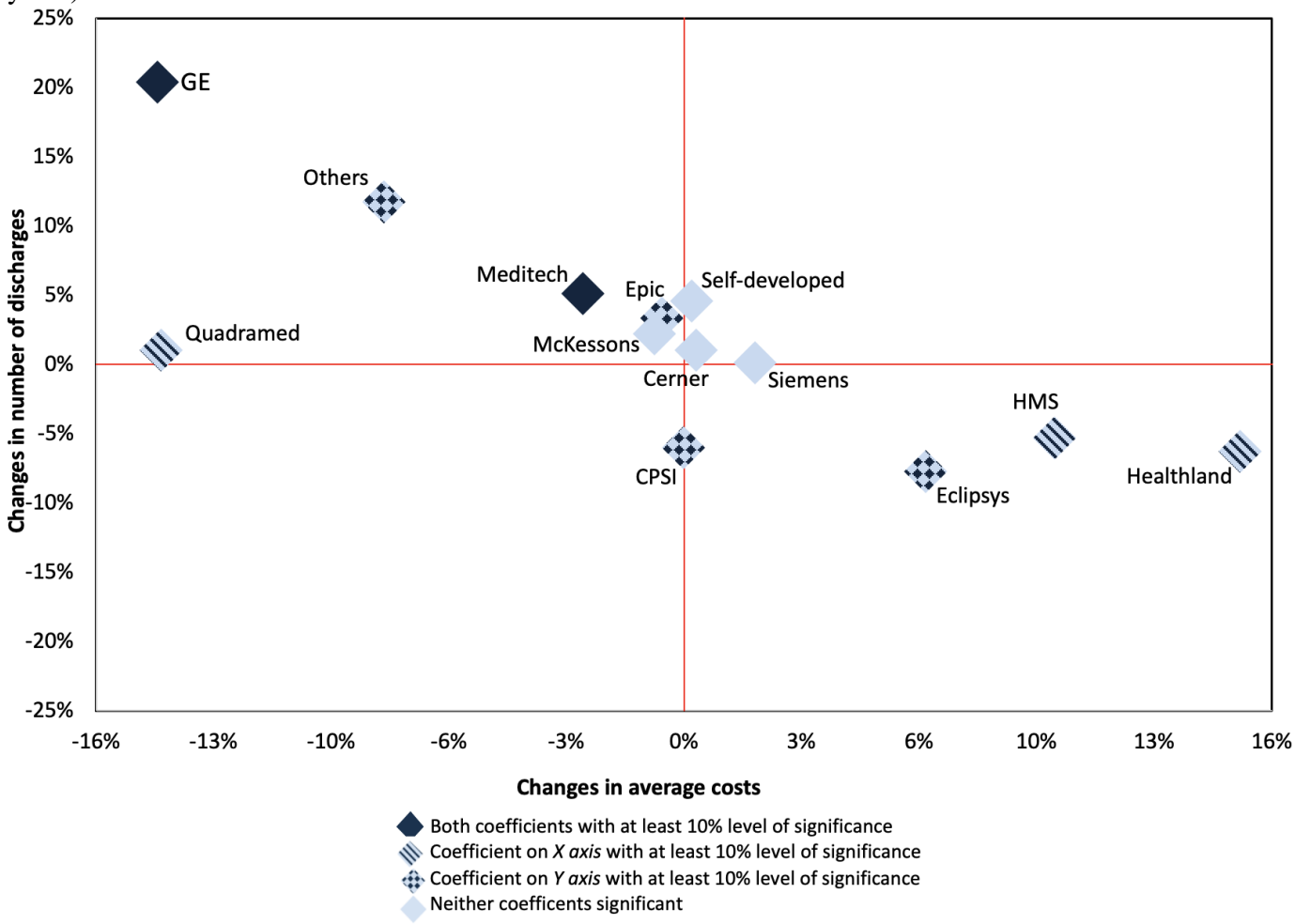


Figure 5: ADE rates (overall) vs. average costs per stay (adoption $\geq$ 3 years)

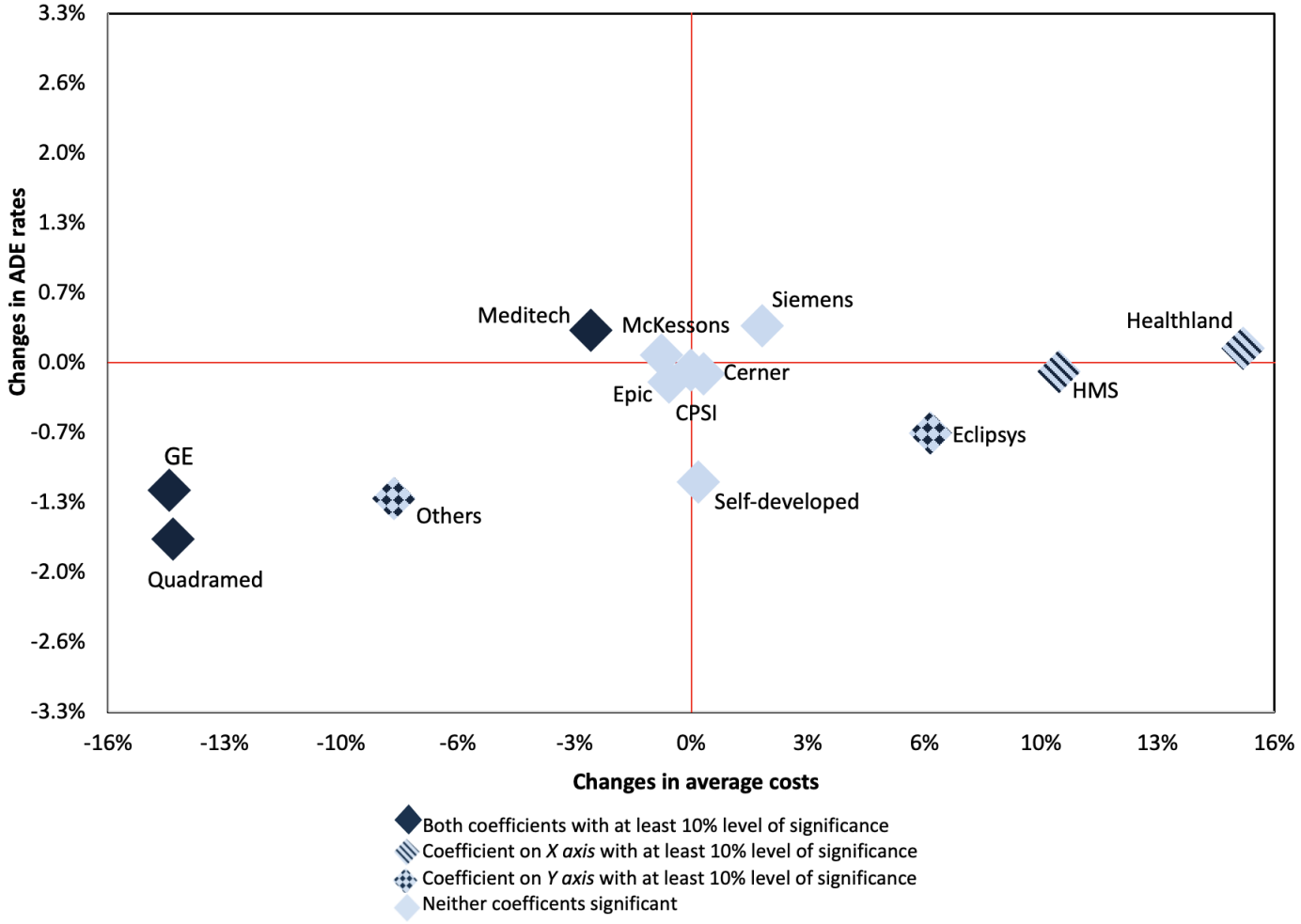
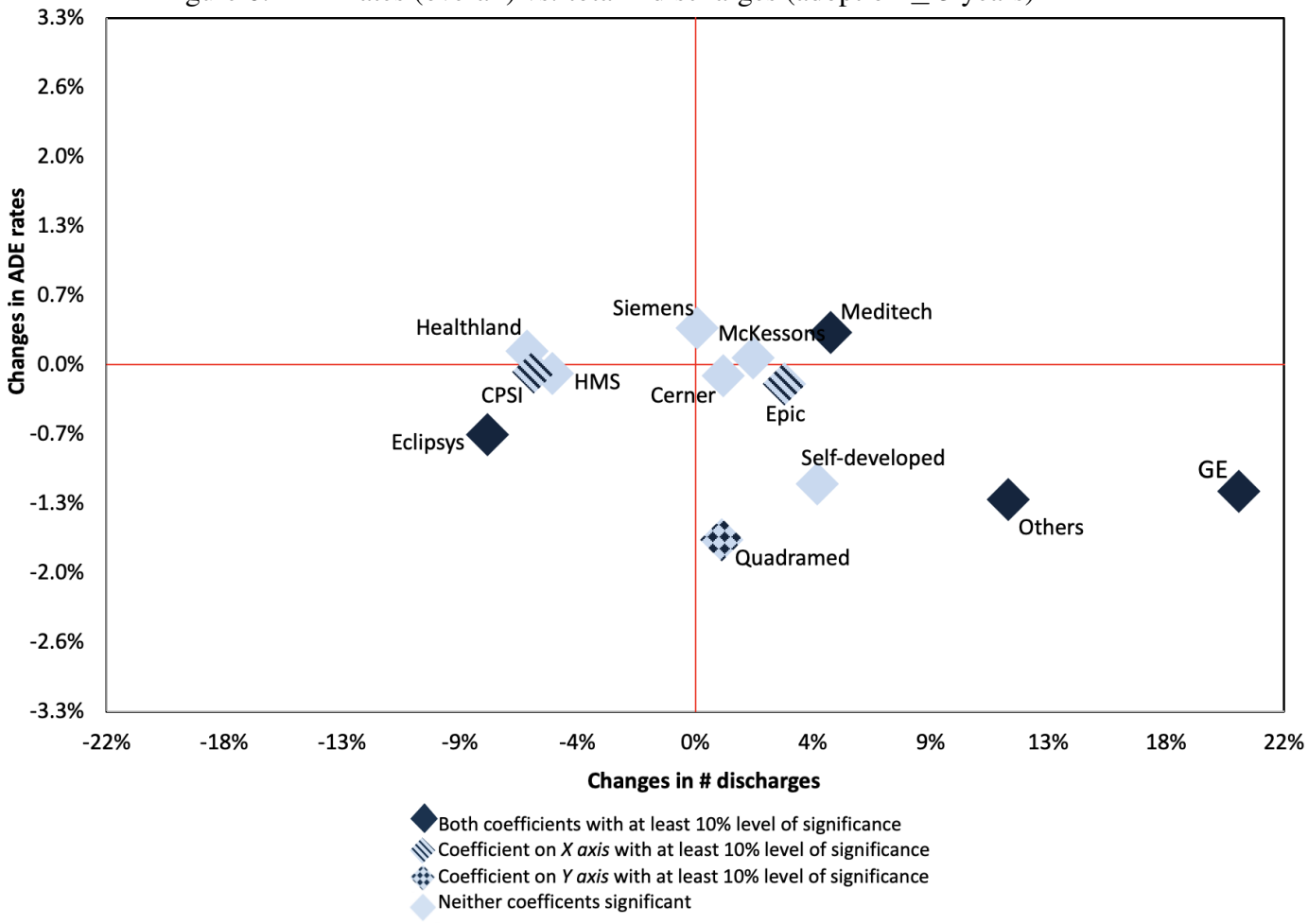


Figure 6: ADE rates (overall) vs. total # discharges (adoption $\geq$ 3 years)



Appendix I: Extra tables and figures

Table A1: Summary of pre-adoption trend analysis

	P values on joint insignificance of pre-adoption periods (*adopters* vs. *non-adopters*)	# out of 13 vendors that are NOT significantly different from *non-adopters*
Financial measures		
Average operational expenses per discharge	0.432	11

Table A2: General adoption effects for operational expenses

	Average operational expenses per discharge	
	(1)	(2)
Adopt	0.00572	
	(0.00493)	
Adopt $<$ 3 years		0.00332
		(0.00497)
Adopt $\geq$ 3 years		-0.0210***
		(0.00811)
N	42761	

Note: Other regressors include an adopter-specific time trend, hospital fixed effects, state-year fixed effects, and a set of hospital and demographic controls. The hospital controls include the following variables valued 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 was ever a critical access hospital, 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. The demographic controls include the following variables valued in 2000 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 average total discharges at the hospital level (over the years of our sample). Standard errors clustered at the hospital level and presented in parentheses.

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

Table A3: Vendor-specific effects — additional measures

	Average operational expenses		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	0.0714*	0.0915***	-0.0154
	(0.0371)	(0.0354)	(0.0288)
Cerner	0.0162	0.0149	-0.000839
	(0.0112)	(0.0113)	(0.0189)
CPSI	0.0246	0.0201	0.0215
	(0.0206)	(0.0206)	(0.0289)
Healthland	0.0328	0.0254	0.0695
	(0.0297)	(0.0282)	(0.0587)
Eclipsys	0.00170	0.00367	0.0235
	(0.0446)	(0.0441)	(0.0883)
Epic	-0.00473	-0.00806	-0.0298*
	(0.0114)	(0.0111)	(0.0172)
GE	-0.0179	-0.0215	-0.0836
	(0.0410)	(0.0414)	(0.0572)
HMS	-0.0366*	-0.0374*	-0.0654
	(0.0211)	(0.0209)	(0.0398)
McKessons	0.0123	0.00973	-0.0117
	(0.0122)	(0.0122)	(0.0197)
Siemens	0.0183	0.0165	0.00683
	(0.0155)	(0.0156)	(0.0232)
Meditech	-0.00371	-0.00581	-0.0330**
	(0.00898)	(0.00895)	(0.0134)
QuadraMed	0.00500	0.00452	-0.0195
	(0.0527)	(0.0501)	(0.0836)
Others	0.0131	0.00480	-0.00808
	(0.0326)	(0.0305)	(0.0436)
N		42761	
P-value for joint insignificance	0.371	0.250	0.243
P-value for joint equality	0.384	0.209	0.549

Notes: Other regressors used to estimate average operational expenses are similar to those used in Table 3 except that we replace adopter-specific time trends with vendor-specific time trends. Clustered standard errors in parentheses.

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

Table A4: Summary of pre-adoption trend analysis, using an alternative adoption definition

	P values on joint insignificance of pre-adoption periods (*adopters* vs. *non-adopters*)	# out of 13 vendors that are NOT significantly different from *non-adopters*
Financial measures		
Average costs per discharge	0.413	10
Quality measures		
ADE rates	0.398	7
Patient volume		
Total # discharges	0.089	9

Table A5: General adoption effects, using an alternative adoption definition

	Average costs per stay		Total # stays		ADE rates	
	(1)	(2)	(3)	(4)	(5)	(6)
Adopt	0.00388		0.00441		0.000786	
	(0.00484)		(0.00538)		(0.000789)	
Adopt $<$ 3 years		0.00398		0.00648		0.000920
		(0.00490)		(0.00538)		(0.000781)
Adopt $\geq$ 3 years		0.00504		0.0278***		0.00224
		(0.00761)		(0.00874)		(0.00157)
N	40316		40326		14695	

Note: Other regressors include an adopter-specific time trend, hospital fixed effects, state-year fixed effects, and a set of hospital and demographic controls. The hospital controls include the following variables valued 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 was ever a critical access hospital, 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. The demographic controls include the following variables valued in 2000 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 average total discharges at the hospital level (over the years of our sample). Standard errors clustered at the hospital level and presented in parentheses.

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

Table A6: General adoption effects, using a new DiD estimation approach

	Average costs per discharge	Logged total # discharges	ADE rates
Adopt	-0.00202	0.00244	0.00213**
	(0.010)	(0.00749)	(0.00102)
N	42,918	42,928	16,155
P value on joint insignificance of pre-adoption periods	0.416	0.208	0.623

Note: Other regressors include an adopter-specific time trend, hospital fixed effects, state-year fixed effects, and a set of hospital and demographic controls. The hospital controls include the following variables valued 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 was ever a critical access hospital, 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. The demographic controls include the following variables valued in 2000 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 average total discharges at the hospital level (over the years of our sample). Standard errors clustered at the hospital level and presented in parentheses.

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

Table A7: Vendor-specific effects — financial measure, using an alternative adoption definition

	Average costs per discharge		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	0.0207	0.00706	0.0414
	(0.0230)	(0.0218)	(0.0286)
Cerner	0.00859	0.00922	0.0141
	(0.0102)	(0.0102)	(0.0153)
CPSI	0.0140	0.0132	0.0118
	(0.0190)	(0.0189)	(0.0277)
Healthland	0.0465	0.0411	0.0977*
	(0.0313)	(0.0291)	(0.0544)
Eclipsys	0.0246	0.0249	0.0762
	(0.0384)	(0.0369)	(0.0539)
Epic	-0.0152	-0.0138	-0.00486
	(0.0118)	(0.0118)	(0.0173)
GE	-0.00894	-0.0165	-0.0525
	(0.0306)	(0.0312)	(0.0456)
HMS	0.0623***	0.0589**	0.113***
	(0.0230)	(0.0233)	(0.0366)
McKessons	0.00348	0.00244	-0.00633
	(0.0119)	(0.0119)	(0.0178)
Siemens	0.00874	0.00844	0.00748
	(0.0163)	(0.0162)	(0.0232)
Meditech	0.00601	0.00522	-0.00370
	(0.00914)	(0.00915)	(0.0135)
QuadraMed	-0.0507	-0.0569	-0.0131
	(0.0594)	(0.0537)	(0.0926)
Others	-0.0200	-0.00663	-0.0765*
	(0.0257)	(0.0224)	(0.0463)
N		40316	
P-value for joint insignificance	0.235	0.356	0.0450
P-value for joint equality	0.251	0.367	0.0400

Notes: Other regressors are the same as to those used in Table 4. Clustered standard errors in parentheses.

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

Table A8: Vendor-specific effects — patient volume, using an alternative adoption definition

	Logged # discharges		
	Overall (1)	Adoption < 3 years (2)	Adoption ≥ 3 years (3)
Selfdeveloped	-0.00199	0.0267	-0.0344
	(0.0281)	(0.0249)	(0.0417)
Cerner	-0.00410	-0.00391	0.00910
	(0.0116)	(0.0115)	(0.0187)
CPSI	-0.0604**	-0.0544**	-0.0733**
	(0.0262)	(0.0265)	(0.0318)
Healthland	-0.00453	0.000208	-0.0144
	(0.0449)	(0.0426)	(0.0726)
Eclipsys	-0.0180	-0.0197	-0.0603
	(0.0212)	(0.0209)	(0.0369)
Epic	0.0291**	0.0308**	0.0475***
	(0.0127)	(0.0126)	(0.0175)
GE	0.0810*	0.0941*	0.172**
	(0.0490)	(0.0522)	(0.0844)
HMS	-0.0333	-0.0326	-0.0167
	(0.0268)	(0.0264)	(0.0485)
McKessons	-0.00769	-0.00660	0.0248
	(0.0124)	(0.0127)	(0.0196)
Siemens	-0.00107	0.0000724	-0.00276
	(0.0182)	(0.0177)	(0.0230)
Meditec	-0.00854	-0.00443	0.0476***
	(0.00962)	(0.00955)	(0.0152)
QuadraMed	0.0120	0.0128	0.0420
	(0.0453)	(0.0446)	(0.0655)
Others	0.0765**	0.0749**	0.128***
	(0.0339)	(0.0362)	(0.0389)
N		40326	
P-value for joint insignificance	0.0523	0.0509	0.0000545
P-value for joint equality	0.0357	0.0349	0.000544

Notes: Other regressors are the same as to those used in Table 5. Clustered standard errors in parentheses.

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

Table A9: Vendor-specific effects — quality measure, using an alternative adoption definition

	ADE rates		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	-0.00439	-0.00410	–
	(0.00280)	(0.00278)	–
Cerner	0.00346*	0.00342*	0.00451
	(0.00209)	(0.00207)	(0.00360)
CPSI	0.00112	0.00138	0.000662
	(0.00324)	(0.00328)	(0.00539)
Healthland	-0.00488	-0.00525*	0.0119*
	(0.00315)	(0.00315)	(0.00682)
Eclipsys	-0.00833*	-0.00844*	-0.00232
	(0.00451)	(0.00446)	(0.00941)
Epic	-0.00168	-0.00144	-0.00815
	(0.00234)	(0.00234)	(0.00613)
GE	-0.00761**	-0.00731**	-0.0138**
	(0.00364)	(0.00353)	(0.00622)
HMS	0.00313	0.00333	0.00282
	(0.00246)	(0.00248)	(0.00562)
McKessons	0.00246	0.00269	0.000821
	(0.00179)	(0.00179)	(0.00332)
Siemens	0.00404*	0.00419*	0.00496
	(0.00225)	(0.00223)	(0.00350)
Meditech	0.00154	0.00157	0.00630***
	(0.00121)	(0.00121)	(0.00234)
QuadraMed	-0.0206**	-0.0185**	-0.0283**
	(0.00947)	(0.00876)	(0.0123)
Others	-0.00611*	-0.00746**	0.00928
	(0.00364)	(0.00290)	(0.0132)
N		14695	
P-value for joint insignificance	0.00183	0.000272	0.00747
P-value for joint equality	0.00121	0.000167	0.00747

Notes: Other regressors are the same as to those used in Table 6. Clustered standard errors in parentheses.

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

Table A10: First stage multinomial conditional logit results for the IV analysis

	Dependent variable: Choice of vendor	
	Time frame: 2006-2017	Time frame: 2006-2010
Vendor share among hospitals within the radius of 30-60 miles	0.913***	0.787***
	(0.0689)	(0.120)
F-(excl inst)	175.9	42.84

Notes: Given that we use a nonlinear first-stage estimation strategy-a multinomial conditional logit regression, some controls from the second stage become redundant (hospital fixed effects) or are not identified (state x year effects). Moreover, including an additional control adds in another 13 coefficients to be estimated (with the interaction with vendor dummies). We test for which control variables from the main specification can be included, and the results are in general robust. Our set of controls in the first stage include the interaction of vendor dummies and the following variables: hospital bed size, and pre- and post-HITECH Act indicators. To keep the non-linear regression model parsimonious, we only use the reported specification. Standard errors in parentheses

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

Table A11: Vendor-specific effects — financial measure, Instrumental Variable Regression Results

	Average costs per discharge		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	0.162*	0.145	0.145
	(0.0975)	(0.0964)	(0.100)
Cerner	0.0588**	0.0599**	0.0602*
	(0.0292)	(0.0290)	(0.0311)
CPSI	0.0966**	0.0987**	0.0802
	(0.0477)	(0.0474)	(0.0523)
Healthland	0.426***	0.405***	0.478***
	(0.140)	(0.140)	(0.144)
Eclipsys	0.151	0.148	0.184
	(0.116)	(0.120)	(0.130)
Epic	-0.0758***	-0.0764***	-0.0583*
	(0.0282)	(0.0283)	(0.0304)
GE	-0.201	-0.211	-0.279*
	(0.157)	(0.157)	(0.163)
HMS	0.223	0.216	0.267
	(0.171)	(0.171)	(0.171)
McKessons	-0.0547	-0.0566	-0.0546
	(0.0776)	(0.0763)	(0.0767)
Siemens	0.0298	0.0314*	0.0421
	(0.0190)	(0.0189)	(0.0265)
Meditec	-0.0384*	-0.0397*	-0.0546**
	(0.0215)	(0.0214)	(0.0235)
QuadraMed	-0.657	-0.612	-0.710
	(0.999)	(1.012)	(1.014)
Others	0.167	0.196	0.143
	(0.140)	(0.139)	(0.146)
N		38546	
P-value for joint insignificance	2.82e-07	4.41e-07	1.52e-06
P-value for joint equality	1.74e-07	2.54e-07	7.03e-07

Notes: Results based on an instrumental variable analyses using a two-stage residual inclusion approach. Regressors include the residuals from the first stage estimation (for each vendor). Other exogenous regressors are the same as those in the Table 4. Clustered standard errors in parentheses.

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

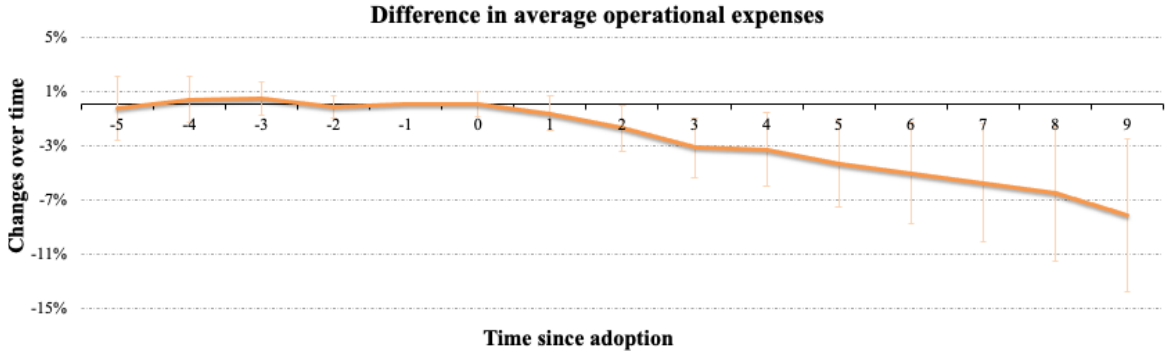
Table A12: Vendor-specific effects — patient volume, Instrumental Variable Regression Results

	Logged # discharges		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	-0.335***	-0.279**	-0.173
	(0.126)	(0.123)	(0.125)
Cerner	0.0335	0.0254	0.0305
	(0.0390)	(0.0387)	(0.0430)
CPSI	-0.246***	-0.253***	-0.249***
	(0.0645)	(0.0645)	(0.0681)
Healthland	0.00824	0.0282	0.0248
	(0.193)	(0.192)	(0.198)
Eclipsys	-0.214*	-0.204*	-0.270**
	(0.117)	(0.119)	(0.123)
Epic	0.0281	0.0184	0.0241
	(0.0318)	(0.0317)	(0.0344)
GE	0.235	0.288	0.435
	(0.333)	(0.337)	(0.345)
HMS	-0.810***	-0.804***	-0.808***
	(0.268)	(0.267)	(0.268)
McKessons	0.186**	0.182**	0.200**
	(0.0833)	(0.0810)	(0.0820)
Siemens	-0.0270	-0.0258	-0.0317
	(0.0183)	(0.0182)	(0.0251)
Meditec	0.0386	0.0412*	0.0839***
	(0.0245)	(0.0244)	(0.0280)
QuadraMed	0.157	0.167	0.206
	(1.576)	(1.561)	(1.565)
Others	-0.318**	-0.366**	-0.301*
	(0.162)	(0.161)	(0.163)
N		38556	
P-value for joint insignificance	1.87e-10	4.54e-10	3.82e-11
P-value for joint equality	8.53e-11	1.99e-10	9.08e-11

Notes: Results based on an instrumental variable analyses using a two-stage residual inclusion approach. Regressors include the residuals from the first stage estimation (for each vendor). Other exogenous regressors are the same as those in the Table 5. Clustered standard errors in parentheses.

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

Figure A1: Trends of operational expenses among adopters and non-adopters



Note: Error bars show 95 percent confidence intervals.

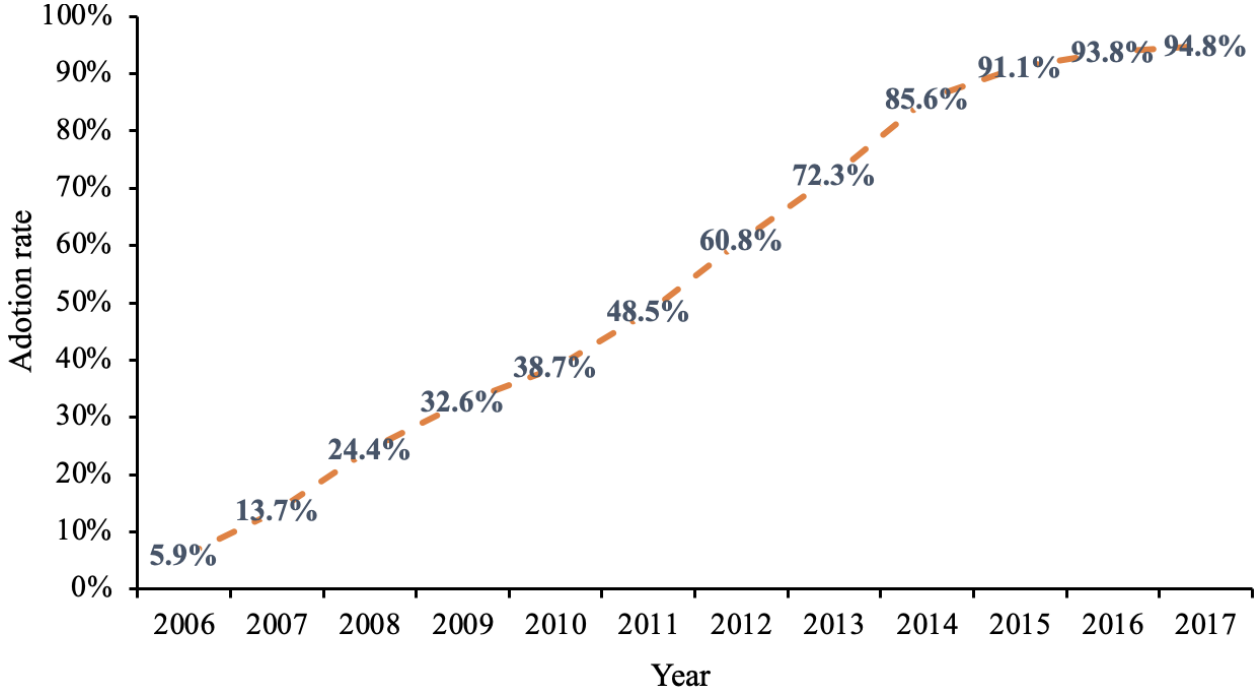
Table A13: Vendor-specific effects — ADEs, Instrumental Variable Regression Results

	ADE rates		
	Overall	Adoption < 3 years	Adoption ≥ 3 years
	(1)	(2)	(3)
Self-developed	-0.0214	-0.0165	–
	(0.0145)	(0.0148)	–
Cerner	0.000159	0.000440	0.00344
	(0.00652)	(0.00665)	(0.00747)
CPSI	0.00916	0.00965	0.00548
	(0.00894)	(0.00887)	(0.0103)
Healthland	-0.0525**	-0.0549**	-0.0460*
	(0.0246)	(0.0247)	(0.0246)
Eclipsys	-0.00933	-0.00962	-0.00686
	(0.00849)	(0.00842)	(0.0112)
Epic	-0.0209*	-0.0202*	-0.0272**
	(0.0112)	(0.0113)	(0.0113)
GE	0.0110	0.0119	0.00334
	(0.00795)	(0.00856)	(0.0109)
HMS	0.0211	0.0203	0.0174
	(0.0239)	(0.0231)	(0.0239)
McKessons	0.0254*	0.0260*	0.0259*
	(0.0134)	(0.0136)	(0.0139)
Siemens	0.00513**	0.00488**	0.00750*
	(0.00231)	(0.00227)	(0.00396)
Meditec	0.00526*	0.00526*	0.00786**
	(0.00299)	(0.00302)	(0.00365)
QuadraMed	-0.288**	-0.329**	-0.338**
	(0.144)	(0.146)	(0.146)
Others	0.0467**	0.0466**	0.112***
	(0.0187)	(0.0186)	(0.0191)
N		14562	
P-value for joint insignificance	0.000123	0.000158	3.70e-08
P-value for joint equality	0.0000646	0.0000848	3.70e-08

Notes: Results based on an instrumental variable analyses using a two-stage residual inclusion approach. Regressors include the residuals from the first stage estimation (for each vendor). Other exogenous regressors are the same as those in the Table 6. Clustered standard errors in parentheses.

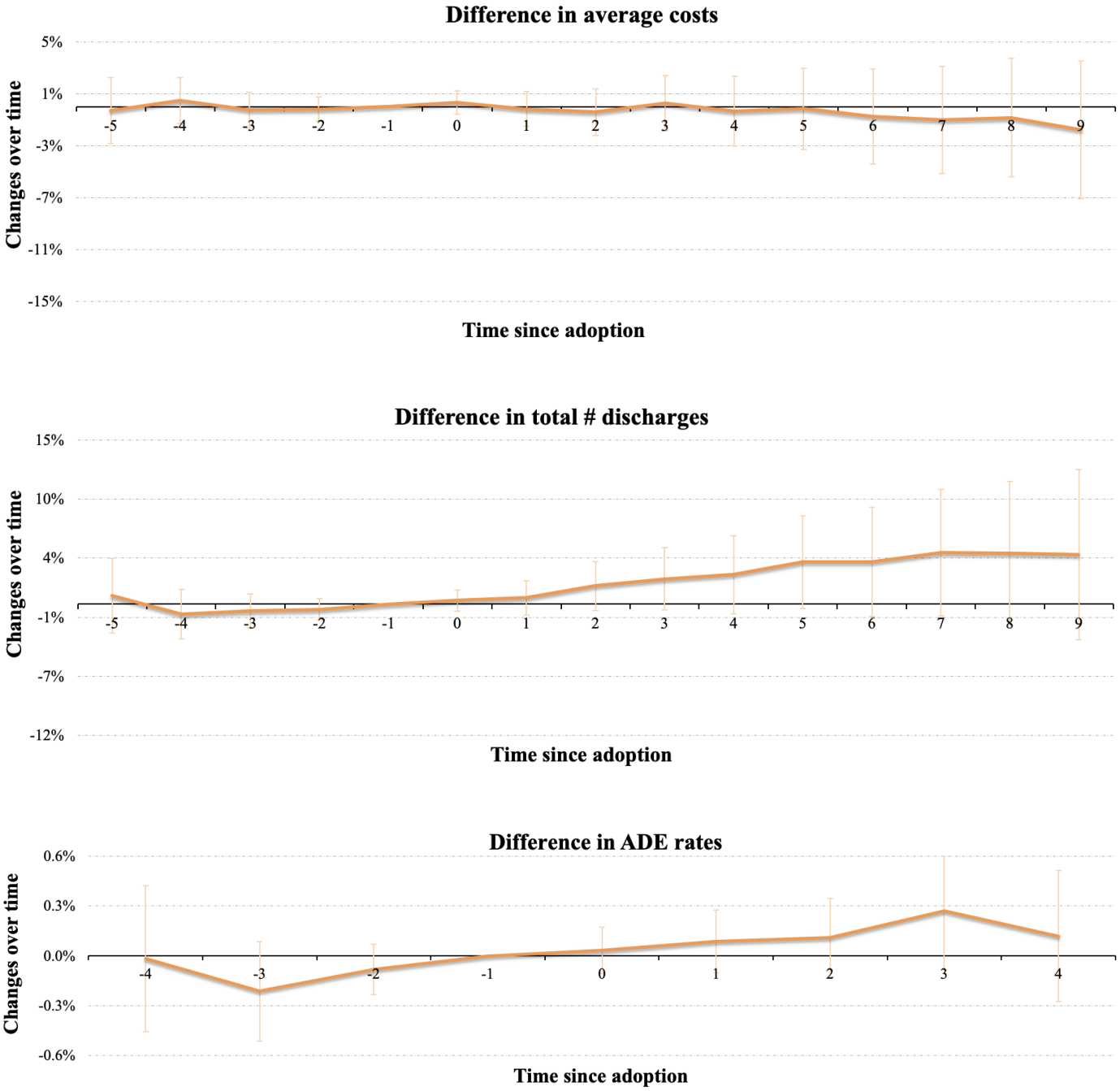
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Adoption rate over time, using an alternative adoption definition



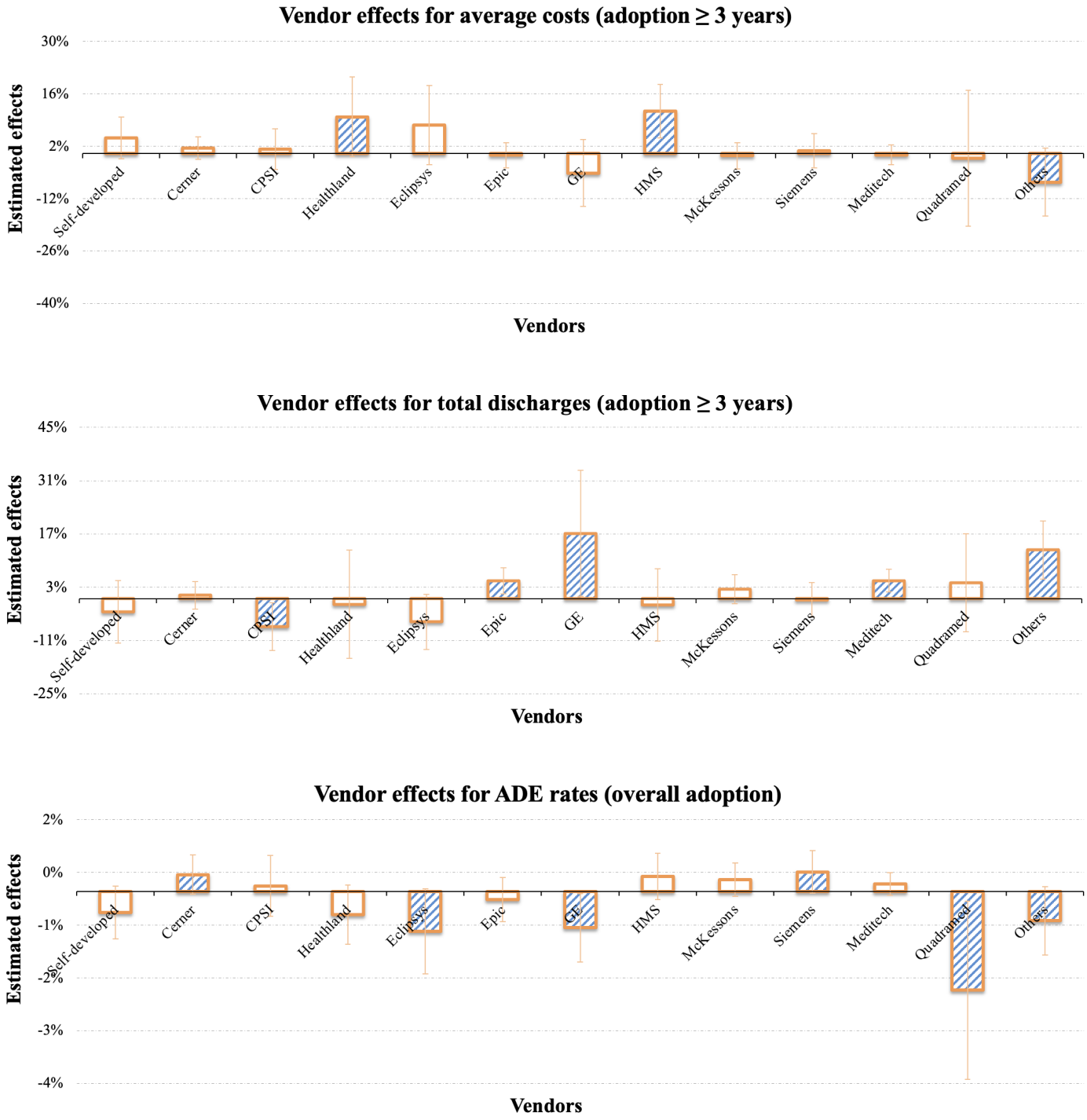
Note: This figure displays the adoption rate of initial adopters of CPOE or PD.

Figure A3: Trends of outcome measures between adopters and non-adopters, using an alternative adoption definition



Note: Error bars show 95 percent confidence intervals.

Figure A4: Vendor heterogeneous effects by outcome, using an alternative adoption definition



Note: The shaded bar suggests that the coefficient has at least 10% level of significance. Error bars show 95 percent confidence intervals.