Does Health IT Save Money and Lives? New Evidence from Vendor Heterogeneity

Jianjing Lin* Mary K. Olson†

November 11, 2018

Preliminary draft

Abstract

This paper examines whether differences among Electronic Medical Record (EMR) vendors and differences in the timing of adoption affect financial and clinical performance in hospitals. Government introduced a 2009 policy that provided $27 billion in subsidies to eligible hospitals and physicians to adopt certified EMRs. However, there is little evidence showing that the technology is producing the anticipated effects. Using data on health IT adoption, Medicare inpatient hospital claims, and hospital characteristics, we examine how vendor heterogeneity affects EMR performance in hospitals. Unlike previous studies we explain hospital vendor choices using an instrumental variables approach. We find that the impact of EMR adoption on Medicare payments and 30 day mortality for Medicare patients varies substantially by vendor. Not all certified EMRs lead to cost savings and/or improved outcomes. These results suggest that the product-related differences among vendors matter and that the government's requirements for "meaningful use" for EMRs could be too general.

JEL Codes:
Keywords: Health IT, hospital billing, health care outcome, Medicare

*Rensselaer Polytechnic Institute; Email: linj17@rpi.edu
†Tulane University

1 Introduction

The diffusion of information technology (IT) in the health sector is expected to reduce costs, improve productivity, and enhance the quality of patient health outcomes. For these reasons, accelerating the pace of health IT (HIT) diffusion has been an important goal of politicians. 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). Thus far, the government has provided $23.5 billion in subsidies under the reform.[1] Although the use of EMRs in hospitals has become widespread, there is little econometric evidence showing that EMRs are reducing costs or producing the anticipated effects. One limitation of prior studies is that they largely neglect the innovative nature of the product and assume products made by different vendors are homogeneous. These assumptions may not be warranted. There is substantial variability in EMR systems between vendors and such variability could potentially impact product performance over time.

This paper examines the extent to which differences among EMR vendors affect the performance of EMRs in hospitals. Examining the impact of EMRs on hospital financial and clinical performance is a particularly interesting issue to study. EMRs allow hospitals to manage and process health care information more efficiently, which in theory may lower health care costs and improve health care quality. Prior research predicted that the benefits emerging from the widespread use of EMRs in hospitals would be substantial (Hillestad et al., 2005). Case studies found positive effects of HIT adoption for select institutions (Chaudhry et al., 2006; Goldzweig et al., 2009; Buntin et al., 2011). With the expectation of improved hospital efficiency and health care quality, policymakers decided to commit substantial resources to the diffusion of EMRs in the 2009 HITECH Act. Unfortunately, more sophisticated econometric studies that included a larger number of hospitals have not found evidence that EMRs reduce costs. Furthermore, such studies also found mixed evidence about the impact of EMRs on clinical outcomes. The limited and mixed evidence of benefits

[1] https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/May2016_SummaryReport.pdf

presents a puzzle for policymakers and raises questions about why EMRs have not lived up to expectations.

We argue that past research has not accounted for the the possibility that differences in the products made by competing vendors may contribute to differences in product performance. These differences can affect profits, growth, and the development of competitive advantages in the EMR industry. Given that EMRs are complex technologies, the products will differ as vendors face variation in customers' demands for new functionalities and improved usability in different markets. That variation could impact performance. In addition to market forces, government policies have strengthened R&D incentives among vendors[2] and raised requirements for EMR systems. The evolving requirements of meaningful use, which set specific objectives that eligible professionals and hospitals must achieve to qualify for Centers for Medicare & Medicaid Services (CMS) Incentive Programs, may also lead to more integrated or complex EMR systems. Increasing complexity may translate into greater heterogeneity among the EMRs offered by vendors, as vendors may devise different ways to meet the new standards. Accounting for such heterogeneity may help shed more light on EMR performance in hospitals.

In addition to differences in EMRs among vendors, the timing of EMR adoption may also impact hospital performance. Given that EMRs are complex products, more experience with a particular system may lead to improved performance of that system over time. Past research showed that the benefits of HIT to certain hospitals only emerge after three years of use, an explanation that is consistent with organizational learning (Dranove et al., 2014).[3]As hospitals build their knowledge base of the HIT product, they may be better able to assimilate the technology in the delivery of patient care. Consequently, hospitals who have more experience with a product (early adopters) may see better performance than hospitals who have less experience with an EMR system (late adopters). In addition to user experience, there may be some benefits associated with the use of newer EMR systems over older sys-

[2]Cerner, a market leader in EMR systems, increased its R&D expenditures from $2 million in 1986 to $226 million in 2005 to $685 million in 2015. McKesson Corporation, another major EMR firm, increased its R&D expenditures from $182 million in 2005 to $392 million in 2015.

[3](Dranove et al., 2014) also show that such benefits only accrue to hospitals in localities with a strong IT infrastructure.

tems. For instance, hospitals who adopt the latest EMR products (late adopters) may also see some gains in performance due to improvements in system quality or ease of use relative to those who are using older EMR systems (early adopters). Although the source of any late adopter advantage is difficult to pin down, accounting for these different effects may help to improve understanding about the impact of EMRs in hospitals.

This paper examines the extent to which vendor heterogeneity and variation in the timing of EMR adoption impacts financial and patient outcomes for U.S. hospitals. We use inpatient hospital claims data for all Medicare patients to construct our measures of costs and patient outcomes. We then merge this data with hospital characteristics extracted from the American Hospital Annual (AHA) survey and HIT hospital IT adoption data from 2006 to 2010 from the Health Information Management System Society (HIMSS) Analytics database. The financial outcomes we examine include Medicare payments, number of total diagnoses, and additional charges relating to pharmaceutical services and radiology services. The patient outcomes we examine include 30-day mortality rates and length of stay.

Our analysis exploits variation in the decision to adopt EMRs and variation among the EMR vendors adopted to explore the differential impacts of EMRs on hospital and patient outcomes over time. We examine the extent to which EMR adoption of a particular vendor affected the outcome relative to what that hospital would have experienced if it hadn't adopted that EMR. One challenge in this estimation is that unobservable factors may impact both the choice of vendor and hospital outcomes, which could bias OLS estimates. For instance, improved hospital performance could be explained by superior managerial ability at the hospital level or it could be due to a particular EMR. We use a two stage IV estimation to address this problem. Our identifying assumption is that our instruments account for provider quality or unobserved market characteristics that may lead our outcome measure to trend differently for adopters relative to non adopters prior to the adoption decision. We first estimate vendor choice as a function of vendor characteristics and instruments, which include vendor firm size, vendor proximity to the hospital, vendor market share in a state and whether the vendor is a market leader in a state. Since the first stage estimation is nonlinear, we employ a residual inclusion method to estimate outcome regressions in the second stage.

We examine whether the effects of EMRs differ among vendors and differ by the timing of EMR adoption. For patient outcomes, we also examine whether the effects differ by patient complexity.

Results show that the impact of EMR adoption on the costs for Medicare patients varies by vendor. Without vendor heterogeneity, hospitals who adopted EMRs see a reduction of 21.3% in Medicare charges on average compared with those without EMRs. With vendor heterogeneity, we observe reductions in Medicare charges for four EMR vendors with the magnitude of the reduction varying considerably. There are some vendors for which EMRs produced no significant impact on Medicare charges and one vendor for which Medicare charges increased with EMR adoption. For the number of diagnoses, we also observe heterogeneous effects. Without vendor heterogeneity, EMRs lead to a decrease of .7% in the number of diagnoses on average compared with those without EMRs. With vendor heterogeneity, we observe reductions in the number of diagnoses for only one EMR vendor, increases in the number of diagnoses for two other EMR vendors, and no significant impacts on the number of diagnoses for the remaining vendors. For pharmacy charges and radiology charges, we also observe heterogeneous effects of EMR adoption by vendor. These results suggest that there may be important differences among the EMRs offered by different vendors and those differences matter in terms understanding whether a hospital will see reductions in costs as a consequence of EMR adoption. Our results relating to the timing of EMR adoption show that cost reductions accrue to both early and late adopters of certain, but not all EMR vendors. They provide further evidence that the differences among the vendors matter in terms of understanding the impact of EMRs on hospital costs. However, we find little evidence of differential effects of experience on EMR performance.

The effect of EMR adoption on Medicare patient outcomes also varies by vendor. Without vendor heterogeneity, EMR adoption is not significantly associated with either length of stay or 30-day mortality rates in general. However, a reduction in mortality was observed for patients with high complexity, namely those who have been previously admitted to the hospital in the last year. This result is consistent with the findings of McCullough et al. (2016) and suggest that EMRs may facilitate care coordination by improving physician access to crucial information from patients' previous hospital admissions. After allowing for vendor heterogeneity, we observe both positive and negative effects of EMRs on patient outcomes. EMR adoption leads to reduced 30 day mortality rates for six EMR vendors, increased mortality for one EMR vendor, and no significant effects among remaining vendors. EMR adoption leads to increased length of stay for two EMR vendors and no significant association among EMR adoption and length of stay for the other vendors. Failure to consider the fact that EMRs are highly differentiated tends to mask the variability in their effects on patient outcomes.

Our results contribute to the economics literature that has examined the value and impact of health IT on hospital financial performance and patient outcomes. Prior literature examining a large number of hospitals hasn't found much evidence of substantial cost savings following EMR adoption. Agha (2014) who examined HIT adoption from 1998 to 2005 found no evidence of cost savings even 5 years after adoption. Dranove et al. (2014) found that on average, hospital operational costs increased immediately following HIT adoption, and only some hospitals eventually experienced a 2.1% to 3.3% reduction in costs three years after HIT adoption.[4] Previous econometric studies have also found mixed evidence about the impact of HIT adoption on patient outcomes. Agha (2014) found negligible impacts of HIT adoption on health care quality measures for Medicare patients. McCullough et al. (2016) found that EMR adoption led to lower mortality rates among Medicare patients with high complexity, and concluded that the benefits from health IT mostly accrue to the cases requiring extensive care coordination and information management. Haque (2014) used a different IT dataset to assess the value of EMRs and found that adoption led to shorter length of stay and reduced mortality for less complex Medicare patients. Two studies of non Medicare patient populations provided additional evidence of clinical benefit from HIT. Miller and Tucker (2011) showed that increased EMR adoption at the county level was associated with a decline in neonatal mortality rates. Freedman et al. (2015) found EMR adoption was associated with fewer preventable adverse events or improved patient safety outcomes, par-

[4] Their results indicated that hospitals in certain locations benefit because of the presence of complementary assets, while those in locations lacking such complementary assets fail to benefit even several years after adoption.

ticularly for patients with less complexity. Our study adds to this literature by introducing vendor heterogeneity and variation in the timing of adoption to better assess the effects of EMR adoption in U.S. hospitals.

Our study provides evidence to help inform the policy debate over government incentive programs for HIT adoption. Such programs have allowed health care providers to 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 results. A policy implication is that the government standards (for meaningful use) may not be sufficient for ensuring the EMR systems deliver in terms of performance.[5]

The remainder of the paper is structured as follows. Section 2 provides the institutional background on EMRs and how they impact the financial and clinical outcomes. Section 3 discusses data sources and section 4 presents the summary statistics. Section 5 describes the estimation methodology and section 6 presents our results. Section 7 offers some concluding remarks.

2 Background

2.1 EMRs and the features of the industry

Health IT has been regarded as a promising tool to improve overall quality and efficiency of the health care delivery system. Electronic Medical Records (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. According to the Healthcare Information and Management Systems Society (HIMSS), a solid EMR system includes 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).

CDR is a centralized database that collects, stores, accesses, and reports health infor-

[5] Holmgren et al. (2017) also provides a similar policy suggestion.

mation, including demographics, lab results, radiology images, admissions, transfers, and diagnoses. Its goal is to provide a full picture of the care that is received by a patient. CDS assists clinicians in decision-making tasks, namely determining the diagnosis or setting treatment plans. It combines computable biomedical knowledge and individual data to recommend specific interventions and assessments and provide other forms of guidance to clinicians. OE is an automated process of entering order information into an electronic billing system. The orders are usually associated with ancillary services such as lab work and radiology. CPOE is a more advanced type of electronic prescribing. It is generally connected with CDS to offer more sophisticated drug safety features such as checking for drug allergies or drug/drug interactions. Both CDS and CPOE require physician involvement to provide real-time support on a range of diagnosis- and treatment-related information. PD offers physicians structured templates to document patient daily progress, operative notes, consult notes, Emergency Department (ED) visits, discharge summaries and other relevant information during the course of admission. Based on the difficulty in implementation and operation, the first three applications (CDR, CDS, and OE) tend to be basic components and the remaining two (CPOE and PD) are advanced applications (Dranove et al., 2014). All the applications are inter-dependent and may even perform overlapping tasks. Therefore, EMRs are complex, enterprise-wide technologies whose implementation could "cause substantive changes in processes, work routines, and established patterns of interaction among organizational actors" (Angst et al., 2010; Brynjolfsson and Hitt, 2000).

Given the complexity of the entire system, products are likely to differ a lot between vendors in various aspects, such as the design of interface and functionalities[6], the level of integration, data storage and organization, practice management, pre-implementation training, IT support and system maintenance. Moreover, each vendor may have its own advantages. Such variations can be translated into differences in user experience that will probably exert different impacts on the practice and change the delivery of care, which will further vary the levels of performance.

[6] Such functionalities may include but not limit to appointment scheduling, medication tracking, ePrescribing, and etc.

EMRs have the potential to increase efficiency and health care quality via a number of mechanisms. The technology collects all patient information in one place, including medical history, diagnoses, medications, treatment plans, immunization dates, allergies, radiology images, lab test results, and etc. Physicians are able to instantly access all relevant information at the point of making decisions, which is essential for safe and effective care. Readily available information also avoids physicians ordering excessive lab work and imaging. Information gathered by EMRs can aid in diagnosis, reduce errors, and improve patient outcomes. For instance, the system with a patient's historical records will automatically check for problems whenever a new medication is prescribed and alert clinicians to potential adverse events. Combining individual records with medical literature, EMRs enable evidence-based decisions and provide reliable guidance. By automating paper-driven and labor-intensive tasks, EMRs streamline clinician work flow, which helps decrease operational costs such as on transcription services, chart refill, and storage. Decreasing operational costs could be a source of efficiency to the hospital, especially if it allows hospitals to treat more patients or more complex patients over time.

However, EMRs may also create new burdens on physicians that may lead to inefficiencies. For instance, new demands on physicians for data entry using computers can use up physicians' time and lead them to see fewer patients. Then even in the presence of some cost savings, EMRs might translate into fewer patients and lower patient revenue, which adversely affects a hospital's bottom line. Such effects could dissipate with time as physicians gain experience with any particular system and become more expert at using it. In addition, some are concerned that EMRs may make it easier to manipulate medical records to increase reimbursement amounts, a practice known as upcoding.[7] Given the range of possible effects, it becomes even more important to empirically study the impact of vendor-specific EMRs in hospitals.

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

2.2 HITECH Act

Information technology has enhanced productivity in many industries such as retail and banking. However, its application in the U.S. health care sector has lagged behind other developed countries (Jha et al., 2008). Only in the last decade have health care providers started to pick up this technology, mostly spurred by the federal incentive program.

President George W. Bush first outlined such a program in 2004 in which most Americans would have electronic health records within 10 years. The president's FY2005 budget proposal included funding for $100 million for demonstrative projects to test the effectiveness of health IT. The Office of the National Coordinator for Health Information Technology (ONC) and the American Health Information Community (AHIC) were established after this proposal and organized a number of meetings with the public and private sectors in 2006-2007 to discuss the prototypes of the Nationwide Health Information Network (NHIN) and strategies to support health IT. These actions and meetings may have increased industry expectations of future subsidies for EMR adoption prior to the actual passage of the Act.

In 2009, the Health Information Technology for Economic and Clinical Health (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 ensure that the technology enhances the overall organizational performance in the health care sector. Participation to the incentive program is voluntary, but failure to demonstrate meaningful use will cause a penalty of 1% Medicare reimbursement staring in 2015 and increase up to 3% in 2017. The program was also available to hospitals who had previously adopted EMRs.

The roll out of the program and the MU requirements was 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.[8] The first stage, launched in 2011, introduced a minimum set core objectives and MU criteria/requirements

[8]Providers must spend two years in a stage before moving on to the next stage.

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. The Centers for Medicare and Medicaid Services (CMS) has adjusted and amended the requirements and deadlines over time to accommodate eligible providers. Stage three requirements are currently being debated. The evolution of these regulations has advanced the development in the health IT industry.

EMR vendors also have to qualify for the certification criteria specified by the Centers for Medicare and Medicaid Services (CMS) and Office of the National Coordinator for Health Information Technology (ONC). The standards and criterion have been published as proposed rules and updated over time according to the stage of the program. Thus, EMR vendors have an opportunity to scrutinize the proposed requirements, comment on them, and adjust their products accordingly. It is likely that the evolving set of the MU requirements have contributed to vendors incentives for R&D and product innovation over time. CMS has even removed several core requirements in the most updated MU criteria, as those have been widely adopted by the industry. While the MU requirements are designed to ensure that each vendor's system meets a common set of objectives, the incentive program, per se, has led to more heterogeneity and advanced innovation in the industry.

3 Data

To examine the effects of vendor heterogeneity and the timing of EMR adoption on financial and patient outcomes for U.S. hospitals in 2006 to 2010, we use data from three sources: the Medicare Provider Analysis and Review (MedPAR) File, the Healthcare Information and Management Systems Society (HIMSS) Analytics Database, and the American Hospital Association (AHA) Annual Survey.

Data from MedPAR is used to develop our financial and patient outcome variables. MedPAR contains information on inpatient hospital stays for all Medicare beneficiaries. Each observation in these data corresponds to an inpatient stay and contains information on the hospital, the beneficiary's home zip code, age, gender, dates of service, reimbursement amount, dates of admission and discharge, Diagnostic Related Group (DRG), and principal and secondary diagnosis and procedure codes. From this data, we construct several financial outcome variables including Medicare payments, number of diagnoses, as well as charges on services like pharmacy and radiology. Our unit of analysis is at the hospital/year level, so each outcome variable is constructed as an annual average across all in sample patients admitted to that hospital in a given year. We also use this data to construct two patient outcome variables, namely 30-day mortality rates and length of stay. Both are significant measures applied by government agencies to assess hospital performance and also commonly studied in the literature.

Our hospital information technology adoption data come from the Healthcare Information and Management Systems Society (HIMSS) Analytics Database. This is a comprehensive, 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. It is an annual survey recording the choice and evolution of a hospital's IT capacities. More specifically, the dataset contains information about a hospital's EMR adoption status, year of adoption, component installed, and identity of the vendor reported in each year from 2006 to 2010.

One challenge in working with these data is that EMRs have multiple components and no uniform definition across studies about which components constitute a functional EMR system. For instance, Jha et al. (2009) divide EMR systems into 32 functionalities, of which they view eight (including some parts of CPOE) as necessary for "basic" EMR operation. Miller and Tucker (2009) measure EMR adoption by whether a hospital has installed an "enterprise EMR" system, which they state is a "basic" system that underlies CDR, CDS, and CPOE. Some studies defined EMR capabilities by either enterprise EMR or CPOE (Lee et al., 2013; McCullough et al., 2016; Ganju et al., 2015). We define a hospital to have adopted

EMRs if any of the components CDR, CDS, CPOE, OE or PD is live and operational in the hospital in a given year. Since it is difficult to precisely identify the impact from any single component, we focus on the system as a whole.

We supplement our technology adoption data with key hospital characteristics obtained from the American Hospital Association (AHA) Annual Survey. The AHA data includes a rich set of hospital-specific features such as hospital beds, outpatient visits, admissions, births, inpatient days, hospital staff, system affiliation, organization structure, ownership status, and other characteristics. We match data from the three sources above using a hospital's Medicare provider number.[9]

We start with approximately 4,900 hospitals per year in the HIMSS analytic database, and the number drops to about 4,500 after merging with AHA annual survey. With five-years of data, there are 22,450 observations in total. We then remove hospitals who were dealing with multiple vendors during the sample period and the total number drops to 18,877.[10] We also remove hospitals that switched more than once over those years, after which there are 18,542 observations remaining.[11] We then remove hospitals whose adoption year is unknown and whose county information is missing, which leaves us 17,679 observations. For each financial outcome, we further exclude non-positive observations, which will become missing values when we take logs in the regression analysis. Since the non-positive values for each outcome may be observed in different hospitals, the number of observations varies between outcomes in the analysis on general adoption (Table 5).[12] In addition, when constructing the instruments in our main analysis, we use lagged variables and lose one year of data, approximately 20% of the observations. Exclusion of non-positive values also contributes to the difference in the number of observations in the vendor-specific analysis, as shown in Table 8 and 9. The number of hospitals also varies in the analysis for mortality rates due to further loss of observations when we construct the index admission[13] for patient

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

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

[11] It is difficult to identify the effect of any particular vendor when a hospital switches several times.

[12] For instance, three observations (three different hospitals, each in a particular year) have non-positive average Medicare payment, and thus, the number of observations for Medicare payment in Table 5 is 17,676.

[13] The index admission is the starting point for analyzing repeat hospital visits. (Healthcare Cost and

quality outcomes. In our sub-analysis which adjusts for patient complexity, the number of observations is further reduced because some hospitals drop out of the sample since they do not have any patients who were previously admitted in the last twelve months.

4 Summary Statistics

Table 1 presents the summary statistics for financial outcome variables. The average Medicare payment is $7,416. The cost of pharmaceuticals is $4,203 on average, while the average charge for radiology services is $1,623. The average number of diagnoses is 8.

Table 2 shows the summary statistics for quality outcomes. The upper panel displays the distribution of 30-day mortality rate while the lower panel for patient length of stay. The definition of 30-day mortality follows the guideline from the CMS[14]. We not only look at the statistics for the entire sample but also examine the mean measure after adjusting the level of complexity. Following the literature, we categorize a complex patient as one who has been admitted in the previous 12 months.[15] Patients with less complexity (who haven't been admitted in the last 12 months) tend to have lower mortality rate.

Table 3 reports the adoption and switching rate over the sample period. The data show that slightly more than 70% of the hospitals had adopted some form of EMRs by 2006 and this number increases to almost 94% by the end of the sample period. The relatively high numbers of adopters by 2006 may reflect two things. First, our definition of adoption refers to hospitals who adopt any single EMR component. Second, industry may have had expectations of a government incentive program for EMRs as early as 2004.[16] We also observe 2 - 4% hospitals switching vendors each year, which is more than 10% changing vendors during our sample period.[17] The variation from new adoption and switching form the major identification power

Utilization Project, 2012). We only include patients whose index admission occurs in our sample period.

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

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

[16] President Bush first proposed a program to incentivize EMR adoption in 2004 and subsequent political efforts reinforced such industry expectations.

[17] The increase in EMR adoption/switching observed between 2006 and 2008 may be caused in part by the expectation of future subsidies for EMRs from prior proposals. The HITECH Act did offer subsidies to

in our estimation.

Table 4 reports summary statistics for hospital characteristics according to EMR adoption status. Early adopters are more likely to be large organizations and associated with academic medical centers. The systematic differences between early and late adopters suggest that separating the effect by the time of adoption could be important in comparing hospital performance. Note that we use 2007 as the cutoff mainly for identification reasons. When we use later years as the cutoff, there are fewer hospitals as new adopters and thus likely to impair accuracy of the estimates.

5 Empirical Strategy

Our empirical specification compares the financial and patient outcomes measures among hospitals who adopted EMRs to non-adopting hospitals over time. We measure the effects of EMR adoption on our outcomes after controlling for adopter-specific time trends, state-year fixed effects, and differential trends by select hospital characteristics (Agha, 2014). We then introduce vendor specific effects. Our analysis proceeds as follows. First, we examine the general impact of EMR adoption on our outcome measures without controlling for vendor heterogeneity. This case, which corresponds to the approach taken in prior research, provides a benchmark for assessing EMR performance. Second, we introduce vendor heterogeneity and examine whether products from different vendors have differential effects on hospital performance. Because unobservable characteristics at the hospital level may impact both the choice of vendor and hospital outcomes, we instrument for a hospital's choice of EMR vendors using a two stage residual inclusion approach. This method is appropriate given the nonlinear estimation required in the first stage IV regression (Terza et al. 2008). Third, we examine how the timing of EMR adoption affects the performance of the EMRs offered by different vendors. We divide the hospitals into early and late adopters of a particular EMR vendor to examine whether difference in experience with EMRs may impact performance. This third specification will allow us to examine the extent to which early adopters of EMR

hospitals who had already adopted EMRs as well as hospitals who were new adopters.

systems derive benefits from having more experience with those systems compared to late adopters.

5.1 No vendor heterogeneity

To identify the general effect of EMR adoption, we estimate the following regression

$$Y_{it} = \beta \text{adopt}_{it} + \theta(\text{adopter}_i \times t) + \alpha_i + \gamma_{st} + \delta X_{it} + \varepsilon_{it} \tag{1}$$

Y_{it} denotes the outcome variable for hospital i in year t. We include hospital fixed effects α_i to control for time-invariant factors at the hospital level that may also influence the outcomes. The variable $\text{adopt}_{it} = 1$ if hospital i adopted an EMR in year t or an earlier year. 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. X_{it} is a vector of characteristics of hospital i at time t. These characteristics include total outpatient visits, outpatient visits squared, total admissions, total births, number of full-time physicians and dentists, percentage of Medicare discharge, percentage of Medicaid discharge, and an indicator for whether the hospital is part of a hospital system, profit status, integration level with physicians (whether a hospital is an independent physician association hospital or whether it is organized as a management service organization), 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. For instance, for-profit hospitals may demonstrate a different pattern in financial performance compared with not-for-profit hospitals. 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-specific time trend.

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

5.2 Vendor-specific effects

Our second specification considers whether vendor heterogeneity plays a role in hospital performance. We will use a two stage IV estimation to examine this issue. Building upon (1) we estimate:

$$Y_{it} = \sum_{k=1}^{K} \beta_k \text{vendor}_{it}^{k} + \theta(\text{adopter}_i \times t) + \alpha_i + \gamma_{st} + \delta X_{it} + \varepsilon_{it} \tag{2}$$

Let k represent a particular vendor from the set of active vendors in the market, $\{1, 2, ..., K\}$. We assume $\text{vendor}_{it}^{k} = 1$ if vendor k is live and operational in hospital i at t. We include 12 major vendors of inpatient EMR systems and group those remaining into a class called "others".[18] These vendor-specific dummy variables will help control for potential variation among EMR systems in terms of interface (how to present patient information and interact with physicians), functionalities (such as appointment scheduling, medication tracking, ePrescribing and etc.), training programs, customer support, and system maintenance (software upgrades) and better determine the impact of these different EMRs on hospital performance. As in (1) we control for hospital fixed effects α_i, state-year fixed effects γ_{st}, a rich set of hospital characteristics X_{it}, and an adopter specific time trend.

It is likely that there are unobservable characteristics affecting both the choice of vendor and hospital outcomes, which could make OLS estimates inconsistent. For instance, unobserved local market or hospital characteristics may appeal to certain vendors, and those characteristics could also influence hospital performance. If there are such unobserved characteristics that correlate with particular vendors and if those characteristics also influence hospital performance, the hospital's vendor choice may be endogenous. To address this issue,

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

we use an instrumental variable approach and two stage residual inclusion estimation.

In the first stage, we use a multinomial logit to estimate a hospital's vendor adoption choice as a function of vendor characteristics and other instruments. We use instruments that are correlated with a hospital's vendor choice in a local market, but have little relation to the unobservables expected to influence hospital performance in that local market. Our instruments are (i) the distance between a vendor and the hospital; (ii) the squared distance between a vendor and the hospital; (iii) the logged revenue of the vendor (in t-1); (iv) the reported research and development expenditure of the vendor (in t-1); (v) reported research and development expenditure of the vendor squared (in t-1); (vi) the reported marketing expenditure of the vendor (in t-1); (vii) reported marketing expenditure of the vendor squared (in t-1); (viii) market share of vendor i (in t-1) in a state in which the hospital is located; (ix) indicator variables for whether a vendor i is the leading vendor in the state (t-1); (x) an indicator for whether vendor i is the 2nd market leader in the state (t-1); (xi) an indicator for whether vendor i is the 3rd market leader in the state (t-1). These instruments may help explain a hospital's vendor choice, but the vendor characteristics and state level market conditions are unlikely to be correlated with hospital outcome measures in a local market. For instance, a hospital may be more familiar with vendors who are geographically close or large in size, and hence more likely to choose such vendors. However, the fact that a vendor happens to be close or relatively big in size is not expected to correlate with hospital performance.

Then in the second stage using the residual inclusion method, the endogenous variables are not replaced by first stage predictors, but instead first stage residuals from (1) are included as regressors in the second stage estimation from (2). Our identifying assumption is that the instruments account for variation in provider quality or unobserved local market characteristics that may lead our outcome measure to trend differently for adopters and non adopters prior to the adoption decision.

The variables of interest are the coefficients for each vendor k, β_k, which assesses the impact of the adoption of vendor k on hospital financial and patient quality outcome measures. For each second stage regression, we are interested in whether vendor heterogeneity matters, or whether $\beta_{k_1} = \beta_{k_2}\ \forall k_1, k_2,\ k_1 \neq k_2$. Each regression includes an F test to determine the joint significance and joint equality of all β_k's.

5.3 Vendor-specific effects, early vs. late adopters

Our third specification examines the impact of early versus late adoption on the performance of EMRs in hospitals. We will use the results to draw insights about whether the benefits of EMR adoption on hospital performance varies by experience with a particular system. Early adopters may see improved performance due to their experience and knowledge in operating the complex technology from a specific vendor. However, coefficient for late adopters will reveal the extent to which those hospitals with less experience also observe benefits from EMR adoption.

Early adopters are defined as those who adopt EMRs prior to 2007. We pick the 2007 cutoff to distinguish between early and late adopters for two reasons. First, those who adopt in 2006 and earlier will have more experience with their respective EMR systems than those who adopt in 2007 and later.[19] Second, using the 2007 cutoff ensures that we will have a sufficient number of later adopters to compare to our early adopters. Late adopters are defined as those who adopt EMR systems in 2007-2010. Among the hospitals who adopt EMRs, some who adopt earlier than 2007 never switch, while others changed or upgraded their systems after 2007. In this analysis, we define the first type as an "early adopter" and the modern upgrader as a "late adopter".[20]

Our third specification examines the extent to which vendor-specific effects on hospital performance differ by the timing of adoption. As in the prior subsection, we perform a two

[19] While the first year of our data is 2006, we can observe the EMR contract year for most of the hospitals who are listed as adopters in 2006. We find that two thirds of the hospitals listed as having EMRs in 2006 had them for two or more years, thus supporting our assumption that early adopters will have more experience with EMR systems than late adopters.

[20] We assume that hospitals who switch vendors and acquire a newer or different system do not benefit from their experience with an older EMR system. It is a reasonable assumption given substantial differences in products between vendors. There is also some empirical evidence to support this assumption. Lin (2017) found hospitals have to bear a significant amount of switching costs in changing vendors, possibly arising from physician resistance and productivity loss. We also estimate the learning curve for the late upgraders and new adopters respectively and found no significant difference between both.

step estimation first estimating the vendor choice as a function of hospital characteristics and instruments using a multinomial logit, and then using the residual from the first stage in the outcome regression below.

$$
\begin{aligned}
Y_{it} = \sum_{k=1}^{K} [\beta_k^{\text{early}}(\text{vendor}_{it}^k \times \text{early}_{it}) + \beta_k^{\text{late}}(\text{vendor}_{it}^k \times \text{late}_{it})] \\
+\theta(\text{adopter}_i \times t) + \alpha_i + \gamma_{st} + \delta X_{it} + \varepsilon_{it}
\end{aligned}
\tag{3}
$$

We define $\text{early}_{it} = 1$ if vendor k was live and operational in hospital i prior to 2007; $\text{late}_{it} = 1$ if vendor k is live and operational in hospital i in or after 2007.[21]

The other variables are as defined in prior specifications. The coefficients of interest are β_k^{early} and β_k^{late}, which measure the effect of early and late adoption of a particular EMR vendor on the outcome. For each vendor k, the magnitude of β_k^{early} and β_k^{late} will provide insight about the relative impact of system novelty versus user experience on the outcome measures.

6 Results

6.1 No vendor heterogeneity

We first provide the regression results for our outcome variables without vendor heterogeneity in Tables 5 - 7 as a benchmark. Results for the financial outcomes are presented in Table 5 while Tables 6 and 7 present the results for 30 day mortality and patient length of stay,

[21] Consider an example for hospital i, which adopted CPSI in 2006 and 2007 but switched to Epic in 2008-2010. In this case, $\text{early}_{it} = 1$, $\text{vendor}_{it}^{CPSI} = 1$, for $t = 2006, 2007$ and $\text{late}_{it} = 1$, $\text{vendor}_{it}^{Epic} = 1$, for $t = 2008, 2009, 2010$. Note, there is a subtle difference between early adopters vs. late adopters and using early versions vs. late versions of the technology. Consider the example given. Hospital i is an early adopter, using an early version of CPSI and late switcher to Epic. Given that resources and experience are not likely to be transferable, we consider this hospital an early adopter of CPSI and a late adopter of Epic. A potential concern with early adopters who switch is that their experience (unlike other early adopters) is truncated. This could create noise in our estimate of the effects of early adoption. However, we find that more than 72% of hospitals that switched from early to late technology had at least 4 years of experience prior to the switch. Hence, those hospitals may still be representative of experienced users.

respectively. For simplicity we report only the coefficient of interest β's, which represents the marginal effects of first EMR adoption on each outcome measure.

Without vendor heterogeneity, results show the adoption of EMRs do lower Medicare payments. In particular, hospitals who adopted EMRs see a larger reduction of 21.3% in Medicare payments compared to hospitals who did not adopt EMRs. In addition, hospitals who adopt EMRs see reductions of 13% for pharmacy charges and 26.1% for radiology services. These results suggest that EMR adoption improves cost efficiency. We also observed that EMR adoption leads to a slight reduction of .7% in the number of diagnoses. EMR adoption has less impact on patient outcomes, as shown in Tables 6. There is no significant association between EMR adoption and 30-day mortality or patient length of stay in general. However, we do observe a reduction in 30-day mortality rates after adjusting for patient complexity. Among patients with greater complexity, defined as those who had a previous hospital admission one year before, the 30-day mortality rate is 0.575% lower among hospitals with EMRs. Among less complex patients, defined as those without a previous hospital admission in the prior year, the reduction in 30-day mortality is 0.176% and only weakly significant. These results are consistent with the view that EMR technology is more likely to improve health outcomes for sicker patients due to better management and coordination of care.

6.2 Vendor-specific effects and early vs. late

We next present the results for our outcome measures accounting for both vendor heterogeneity and instrumenting for vendor choice. Results from our first stage estimation of vendor choices are presented in Table A1 and suggest that our instruments are suitable.[22] Table 8 contains the regression results related to Medicare payments and number of diagnoses. Each outcome corresponds to three columns of coefficients. The first column presents the estimates of vendor-specific effects (β_k's in Equation (2)) and the second and third columns present the estimates of the interactions with adopting early (β_k^{early}'s in Equation(3)) or late (β_k^{late}'s in

[22]The F on the omitted instruments is 856.

Equation(3))). Each row shows the coefficients for a particular vendor and at the bottom of each column are the p values associated with the tests for joint significance and joint equality of the vendor-specific coefficients. Table 9 presents similar results related to pharmacy charges and radiology charges.

We begin by examining the results in the first column for each outcome in Table 8. Results show that the impact of EMR adoption on Medicare payments varies substantially by vendor. With vendor heterogeneity, we see that a reduction in Medicare charges is only observed for the EMRs from some vendors (five vendors) and the magnitude of the reduction widely varies. Among the hospitals who adopt other vendors, EMRs have either no significant impacts on Medicare payments or a positive impact on Medicare payments (one vendor). These results are depicted graphically in the first plot in Figure 1. The names of the vendors are placed on the X-axis and the estimates and their confidence intervals are plotted along the Y-axis, with each dot representing the point estimate and the bar showing the 95% confidence interval. The graphs provide a visual presentation of the differential effects between vendors. For total number of diagnoses, we also observe variation in the effects of EMR adoption by vendor. With vendor heterogeneity, we see a reduction in the number of diagnoses for one EMR vendor and increases in the number of diagnoses for two other EMR vendors. Among the hospitals who adopt other vendors, EMRs have no significant impacts on the number of diagnoses. These results are depicted graphically in Figure 2.

Results in Table 9 provide further evidence that the impact of EMR adoption on pharmacy charges and on radiology charges vary by vendor. With vendor heterogeneity, we see a reduction in pharmacy charges for four EMR vendors and no significant impact for the other vendors. These results are depicted graphically in Figure 3. With vendor heterogeneity, we see a reduction in radiology charges for ten EMR vendors and no significant effect for the other vendors. The results are depicted graphically in Figure 4. The p-values at the bottom of each column in Tables 8 and 9 indicate that we can reject that the vendor effects are jointly zero and that the vendor effects are jointly equal for our outcome measures at conventional significance levels for Medicare charges and radiology charges and weak significance levels for number of diagnoses and pharmacy charges. This evidence suggests that the differences between EMR vendors matter and not all vendors have the same effect on a hospital's financial performance.

There appears to be relatively limited variation of EMRs on hospital performance by the timing of adoption. The second and third columns for each outcome in Table 8 present the vendor-specific effects interacted with indicators for whether the hospital was an early or a late EMR adopter. Coefficients for each vendor reveal the extent to which any improved performance may be due to more user experience (early adopter) or whether those advantages also fall upon those with less experience (late adopter). For Medicare payment, the early adopters of one vendor see cost savings, which we suggest arises from greater user experience. For four other vendors the cost savings in Medicare payments accrue to both early and late adopters, which suggests that cost savings are not limited to those with experience. Not all EMR vendors result in lower Medicare charges for either early or late adopters. Results show that early and late adopters of one vendor are associated with increases in Medicare payments; while the early and late adopters of seven other vendors are not associated with any significant change in Medicare payments. The last two plots in Figure 1 present these results graphically.

For pharmacy and radiology charges, we also find that the benefits from EMRs are not limited to those with experience as both the early and late adopters of certain vendors experience reduced charges. However, for other vendors there is no significant association between EMR adoption and pharmacy or radiology charges. This range of effects provide further evidence that the differences among the vendors matter in terms of understanding the impact of EMRs on hospital costs.

We find evidence that EMR adoption of certain vendors has affected 30-day patient mortality. Table 10 presents 3 sets of results: vendor effects for all patients without adjustment for complexity; vendor effects for complex patients; and vendor effects for patients not deemed complex. Among all patients, the EMRs from six vendors are associated with a reduction in 30-day mortality rate, ranging from 2.2% to 3.0%. When we separately examine the difference by the timing of adoption, the early adopters of four vendors experience reductions in 30-day mortality, ranging from 2.2% to 3.0%; while the late adopters of six vendors experience reductions in mortality, ranging from 2.0% to 2.9%. We also observe that the early and late adopters of one vendor experienced increased 30-day mortality. The vendor effects are jointly significant and we are able to reject their joint equality in each case. Among complex patients, defined as those who have been admitted into a hospital within the last 12 months, we observe slightly larger effects of select vendors on 30 day mortality. EMRs from five vendors are helpful in reducing mortality rates by a range of 3.4% to 5.2%. The benefits of reduced mortality accrue to early adopters of three vendors and late adopters of six vendors. The results among less complex patients are similar to the effects observed for all patients without adjustment for complexity. The p values at the bottom of each column indicate for 6 of the 9 columns, we can reject that the vendor effects are jointly zero and jointly equal. These results are depicted graphically in Figures 5, 6, and 7. In contrast, Table 11 and Figures 8, 9, and 10 show that EMR adoption of most vendors is not significantly associated with patient length of stay.

7 Conclusion

Although the U.S. government has devoted substantial resources to incentivize the adoption of EMRs by hospitals and physicians, there is little systematic evidence showing that the technology is producing the anticipated cost savings or outcome improving effects. We argue that previous research has not accounted the possibility that differences in the products made by competing vendors may contribute to differences in product performance. Our paper examines how EMR vendor heterogeneity impacts financial and clinical outcomes in U.S. hospitals. Unlike previous studies we explain hospital vendor choices using a two stage IV approach that relies on variation in vendor characteristics to explain vendor choices. Our analysis examines how differences in the timing of EMR adoption may impact hospitals' financial and clinical performance. We also examine the extent to which the changes in hospital performance may be driven by user experience with a vendor's product.

We find that the impact of EMR adoption in hospitals varies substantially by vendor. We observe reductions in Medicare payments arising from the adoption of five EMR vendors with much variation in the magnitude of the effect. We also observe increases in Medicare payments arising from the adoption of one vendor. The variability of these effects is contrasted with the results of prior studies that found modest or negligible effects of EMR adoption on hospital financial outcomes. We also observe heterogeneity in the effects of different vendors on total diagnoses, pharmacy charges, and radiology charges. Our results suggest that there are important differences among the EMRs offered by different vendors and those differences matter in terms understanding whether a hospital will see reductions in costs as a consequence of EMR adoption. Our results relating to the timing of EMR adoption provide little evidence that experience with a vendor's product translates into cost savings. Instead the effects of EMR adoption arise for both early and late adopters of certain EMRs. Our results suggest that the differences among the vendors is important for understanding the impact of EMRs on hospital financial outcomes.

Our results show that the effects of EMR adoption on 30-day patient mortality also varies by vendor. Without vendor heterogeneity, EMR adoption is not significantly associated with 30-day mortality rates among all Medicare patients, but it is associated with a reduction in mortality for patients with high complexity. After allowing for vendor heterogeneity, we observe that EMR adoption reduced 30 day mortality rates for six EMR vendors. These effects were somewhat larger for complex patients. For one other vendor, EMR adoption led to increased 30 day mortality. Our results suggest that a failure to consider the differences among vendors may mask the variability in the effects of EMRs on hospital performance and patient outcomes.

There are a couple caveats to our study. First, given the way we construct our instruments, we lose one year of data (2006). This reduces the variation for identification. In addition, if the adopters in 2006 are systematically different from those in 2007 or later years, then our results may not be fully reflective of the full range of hospitals. However, after comparing the characteristics of adopters in 2006 with adopters in later years and find no significant difference. Second, the patient outcome measures that we examine are two that have received much attention in the literature, yet there remain additional patient outcomes that could be studied. Future research could evaluate the effects of vendor heterogeneity on more refined patient outcomes, such as the mortality rate or complication rate for specific medical conditions, to better assess EMR performance in hospitals.

Our results also have some important policy implications. U.S. policy has allowed hospitals to receive subsidies for a variety of "certified" EMR vendors, as long as those systems meet the conditions of "meaningful use". Given the variability in the effects of different EMR vendors on hospital performance measures, our results suggest that not all certified EMRs are producing the anticipated results. A policy implication is that the government standards (for meaningful use) may be too general or at least not sufficient for ensuring that EMR systems deliver in terms of performance.

References

Agha, L. (2014). The effects of health information technology on the costs and quality of medical care. *Journal of health economics*, 34:19–30.

Angst, C. M., Agarwal, R., Sambamurthy, V., and Kelley, K. (2010). Social contagion and information technology diffusion: the adoption of electronic medical records in us hospitals. *Management Science*, 56(8):1219–1241.

Brynjolfsson, E. and Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *The Journal of Economic Perspectives*, 14(4):23–48.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., and Blumenthal, D. (2011). The benefits of health information technology: a review of the recent literature shows predominantly positive results. *Health affairs*, 30(3):464–471.

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., Morton, S. C., and Shekelle, P. G. (2006). Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. *Annals of internal medicine*, 144(10):742–752.

Dranove, D., Forman, C., Goldfarb, A., and Greenstein, S. (2014). The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy*, 6(4):239–270.

Freedman, S., Lin, H., and Prince, J. (2015). Information technology and patient health: Analyzing outcomes, populations, and mechanisms. Technical report, National Bureau of Economic Research.

Ganju, K., Atasoy, H., and Pavlou, P. (2015). Does the adoption of electronic medical record systems inflate medicare reimbursements? *Working paper*.

Goldzweig, C. L., Towfigh, A., Maglione, M., and Shekelle, P. G. (2009). Costs and benefits of health information technology: new trends from the literature. *Health Affairs*, 28(2):w282–w293.

Haque, R. (2014). Technological innovation and productivity in service delivery: Evidence from the adoption of electronic medical records. *Working paper*.

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., and Taylor, R. (2005). Can electronic medical record systems transform health care? potential health benefits, savings, and costs. *Health affairs*, 24(5):1103–1117.

Holmgren, A. J., Adler-Milstein, J., and McCullough, J. (2017). Are all certified ehrs created equal? assessing the relationship between ehr vendor and hospital meaningful use performance. *Journal of the American Medical Informatics Association*, 25(6):654–660.

Jha, A., DesRoches, C., Campbell, E., Donelan, K., Rao, S., Ferris, T., Shields, A., Rosenbaum, S., and Blumenthal, D. (2009). Use of electronic health records in us hospitals. *New England Journal of Medicine*, 360(16):1628–1638.

Jha, A. K., Doolan, D., Grandt, D., Scott, T., and Bates, D. W. (2008). The use of health information technology in seven nations. *International journal of medical informatics*, 77(12):848–854.

Lee, J., McCullough, J. S., and Town, R. J. (2013). The impact of health information technology on hospital productivity. *The RAND Journal of Economics*, 44(3):545–568.

Lin, J. (2017). Strategic complements or substitutes: The case of adopting electronic medical records (emrs) by us hospitals. *Working Paper*.

McCullough, J. S., Parente, S. T., and Town, R. (2016). Health information technology and patient outcomes: the role of information and labor coordination. *The RAND Journal of Economics*, 47(1):207–236.

Miller, A. and Tucker, C. (2009). Privacy protection and technology diffusion: The case of electronic medical records. *Management Science*, 55(7):1077–1093.

Miller, A. R. and Tucker, C. (2011). Can health care information technology save babies. *Journal of Political Economy*, 119(2):289–324.

Table 1: Summary statistics for financial outcomes among hospitals

Variable	Obs	Mean	Std. Dev.	Min	Max
Medicare payment ($)	17,676	7,416	5,528	431	74,036
Number of diagnoses	17,679	8	1	1	12
Pharmacy charge ($)	17,559	4,203	5,932	0	204,957
Radiology charge ($)	17,506	1,623	1,376	0	12,702

Table 2: Summary statistics for patient quality outcomes among hospitals

	30-day mortality rate				
Sample	Obs	Mean	Std. Dev.	Min	Max
All	17,612	0.0341	0.0242	0	0.597
Patients NOT previously admitted in the last 12 months	13,073	0.0304	0.0258	0	0.587
Patients previously admitted in the last 12 months	13,072	0.0386	0.0297	0	0.577
	Length of stay				
Sample	Obs	Mean	Std. Dev.	Min	Max
All	17,679	5.93	16.74	1	1,626
Patients NOT previously admitted in the last 12 months	13,084	5.60	7.51	1	439.26
Patients previously admitted in the last 12 months	13,079	5.68	10.04	1.06	812.08

Note: Only four of five year data is available for the subsample (previously admitted and not previously admitted in the last 12 months).

Table 3: Summary statistics for adoption and switching rate

	Obs	Adoption rate	Switching rate
2006	3,648	70.1%	–
2007	3,623	84.9%	1.77%
2008	3,490	89.0%	2.98%
2009	3,474	92.1%	4.06%
2010	3,444	93.6%	2.41%

Table 4: Summary statistics on hospital characteristics by EMR use

	Adopters earlier than 2007, never switch	Adopters earlier than 2007, switched during 2007-2010	New adopters during 2007-2010	EMR non-adopters through 2010
Staffed beds	191	195	128	50
Outpatient visits	141,857	136,632	107,221	33,396
Admissions	8,446	9,154	5,710	1,362
Births	968	1,117	629	127
Inpatient days	46,320	47,194	30,773	10,005
Full-time physicians - - and dentists	15	23	18	5
% of Medicare discharge	47.3	46.9	50.3	56.0
% of Medicaid discharge	17.7	17.5	16.1	13.8
Not-for-profit hospitals	0.643	0.700	0.598	0.386
For-profit hospitals	0.234	0.172	0.136	0.146
Equity model hospital	0.0228	0.0117	0.0139	0.0185
Foundation hospital	0.0375	0.0643	0.0475	0.0513
Independent practice - - association hospital	0.148	0.105	0.124	0.179
Management service - - organization hospital	0.0933	0.0526	0.0718	0.0144
Residency or Member of - - Council Teaching Hospitals	0.0639	0.106	0.0544	0.0057
Affiliated to a hospital system	0.527	0.500	0	1
Number of hospitals	2,378	180	919	526

Note: For each set of hospitals, table reports the mean value of statistic over years in our data.

Table 5: General adoption effects — financial outcomes

	Log (Medicare payment)	Log (number of diagnoses)
adopt	-0.213***	-.007**
	(0.0508)	(0.00353)
N	17676	17679
	Log (pharmacy charge)	**Log (radiology charge)**
adopt	-0.130***	-0.261***
	(0.0486)	(0.0636)
N	17,559	17,506

Table 6: General adoption effects — 30-day mortality rate

	All conditions		
	No complexity adjustment	Patients admitted in the last 12 months	Patients NOT admitted in the last 12 months
adopt	-0.000818	-0.00575***	-0.00176*
	(0.000698)	(0.00196)	(0.00102)
N	17612	13072	13073

Table 7: General adoption effects — Length of stay

	All conditions		
	No complexity adjustment	Patients admitted in the last 12 months	Patients NOT admitted in the last 12 months
adopt	0.00641	0.0126	0.0125
	(0.00648)	(0.00793)	(0.00792)
N	17679	13079	13084

Table 8: Vendor-specific effects — financial outcomes

	Medicare payment			Number of diagnoses		
	General	Early	Late	General	Early	Late
Self-developed	-0.823**	-0.787**	-0.869**	-0.0113	-0.00666	-0.00375
	(0.350)	(0.347)	(0.349)	(0.0824)	(0.0825)	(0.0847)
Cerner	-0.536***	-0.487**	-0.579***	-0.0449	-0.0380	-0.0467
	(0.196)	(0.200)	(0.201)	(0.0540)	(0.0549)	(0.0541)
CPSI	-0.298*	-0.780***	-0.233	0.111**	0.104*	0.112**
	(0.176)	(0.262)	(0.166)	(0.0556)	(0.0552)	(0.0556)
Healthland	-0.235	-0.466	-0.175	-0.135	-0.118	-0.146
	(0.355)	(0.369)	(0.357)	(0.0988)	(0.0975)	(0.0990)
Eclipsys	-0.619**	-0.646**	-0.524*	0.151*	0.154*	0.137
	(0.263)	(0.270)	(0.276)	(0.0855)	(0.0854)	(0.0855)
Epic	-0.909***	–	-0.912***	-0.0233	–	-0.0246
	(0.274)	–	(0.271)	(0.0759)	–	(0.0758)
GE	-0.296	-0.347	-0.397	-0.181*	-0.175	-0.199*
	(0.420)	(0.435)	(0.418)	(0.109)	(0.109)	(0.108)
HMS	0.763**	0.688*	0.775**	-0.100	-0.151	-0.102
	(0.356)	(0.356)	(0.354)	(0.112)	(0.111)	(0.111)
McKessons	-0.230	-0.316	-0.147	0.0484	0.0497	0.0446
	(0.193)	(0.200)	(0.194)	(0.0541)	(0.0542)	(0.0549)
Siemens	-0.0969	-0.0899	-0.113	0.0989	0.0981	0.0931
	(0.291)	(0.298)	(0.296)	(0.0742)	(0.0743)	(0.0752)
Meditec	0.115	0.0187	0.115	-0.0178	-0.0219	-0.0157
	(0.169)	(0.187)	(0.171)	(0.0466)	(0.0477)	(0.0465)
Quadramed	0.449	0.411	0.499	0.199	0.201	0.204
	(0.883)	(0.891)	(0.885)	(0.186)	(0.186)	(0.186)
Others	0.177	0.156	0.363	0.0721	0.0809	0.0568
	(0.281)	(0.288)	(0.287)	(0.0877)	(0.0873)	(0.0873)
N	13605	13605	13605	13607	13607	13607
P-value for joint significance	5.14e-09	0.0000151	2.36e-09	0.0514	0.0266	0.0643
P-value for joint equality	3.73e-09	0.0000151	1.24e-09	0.0700	0.0266	0.0803

Standard errors in parentheses

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

Figure 1: Medicare payment

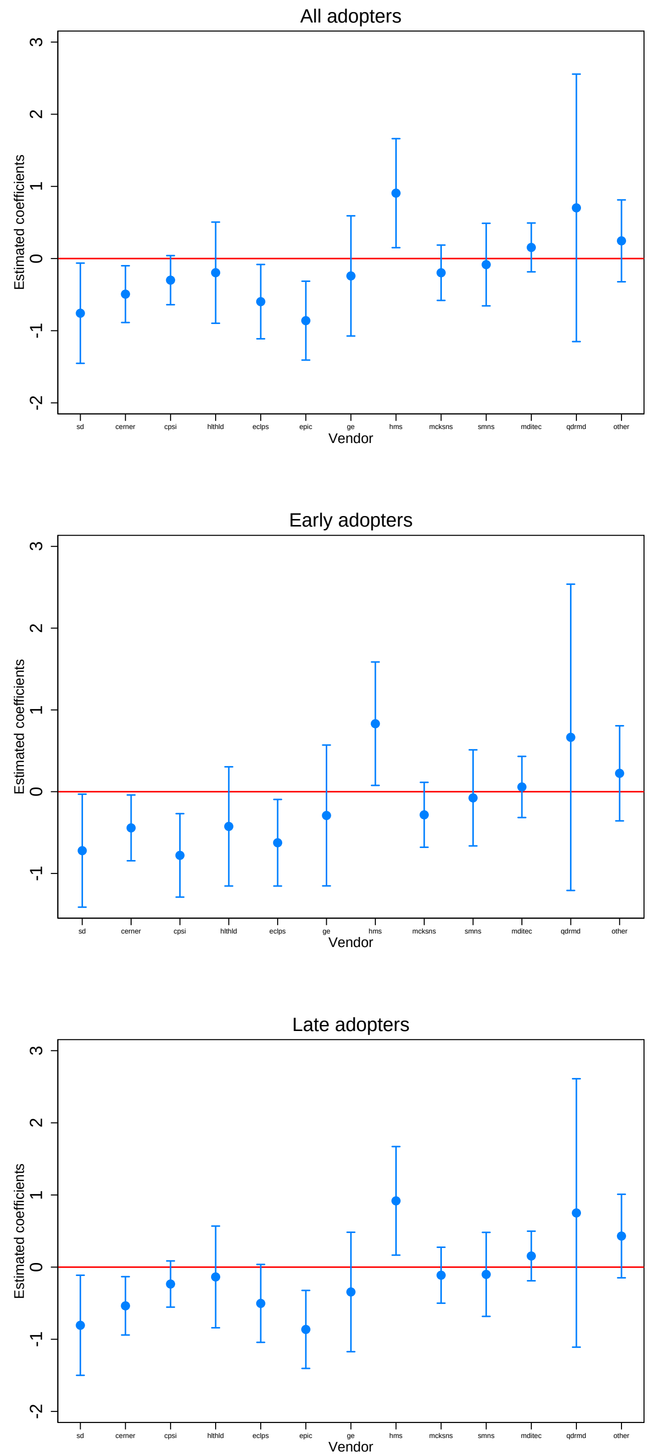


Figure 2: Number of diagnoses

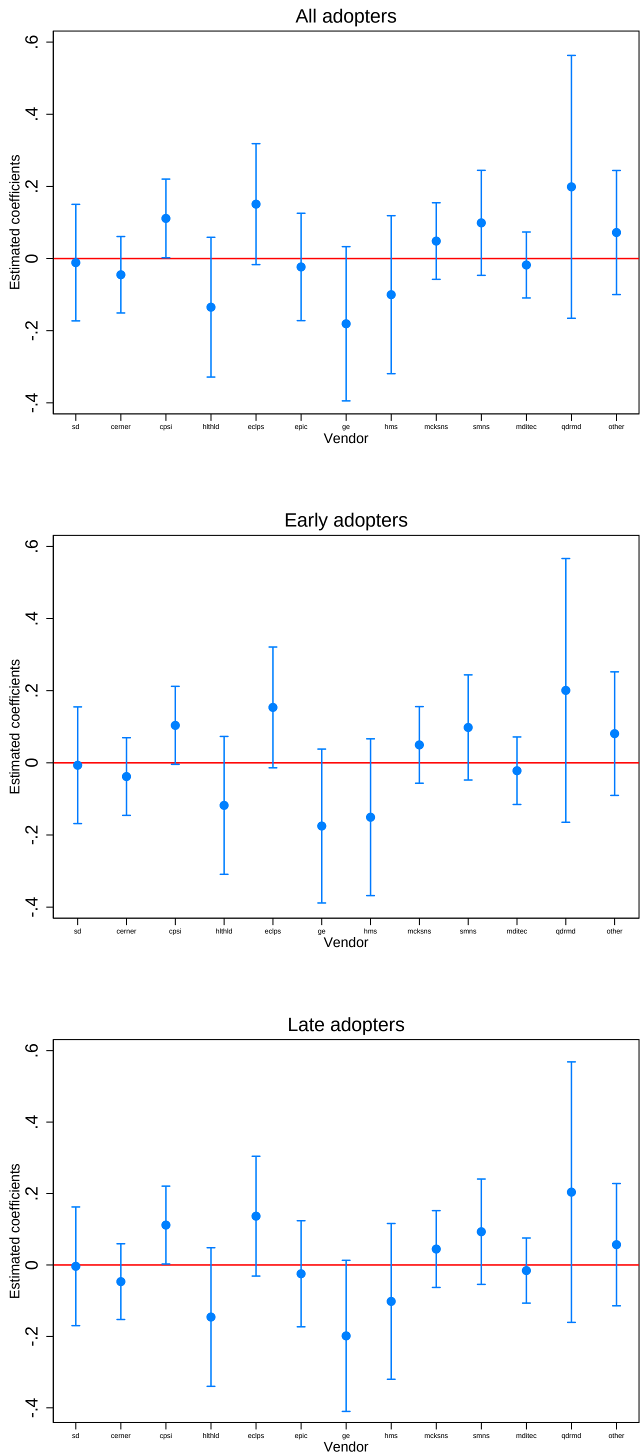


Table 9: Vendor-specific effects — financial outcomes (continued)

	Pharmaceutical charge			Radiology charge		
	General	Early	Late	General	Early	Late
Self-developed	-0.996***	-0.963**	-1.082***	-1.742***	-1.680***	-1.786***
	(0.379)	(0.378)	(0.354)	(0.406)	(0.402)	(0.394)
Cerner	-0.537**	-0.488*	-0.556**	-0.801***	-0.644***	-0.870***
	(0.261)	(0.260)	(0.267)	(0.239)	(0.239)	(0.245)
CPSI	-0.241	-0.514**	-0.211	-0.449**	-0.997***	-0.370*
	(0.218)	(0.262)	(0.215)	(0.214)	(0.312)	(0.198)
Healthland	0.0351	0.00960	0.0719	-0.881**	-0.956**	-0.795*
	(0.376)	(0.398)	(0.377)	(0.418)	(0.426)	(0.425)
Eclipsys	-0.395	-0.452	-0.253	-1.020***	-1.050***	-0.831***
	(0.471)	(0.475)	(0.471)	(0.304)	(0.308)	(0.305)
Epic	-0.861**	–	-0.867**	-1.772***	–	-1.786***
	(0.349)	–	(0.352)	(0.314)	–	(0.305)
GE	-0.693	-0.689	-0.804*	-0.458	-0.535	-0.528
	(0.445)	(0.446)	(0.449)	(0.404)	(0.416)	(0.436)
HMS	-0.0448	-0.125	-0.0573	-0.138	-0.0287	-0.119
	(0.434)	(0.460)	(0.432)	(0.405)	(0.414)	(0.406)
McKessons	-0.438*	-0.479*	-0.370	-0.646***	-0.764***	-0.489**
	(0.240)	(0.247)	(0.244)	(0.230)	(0.235)	(0.231)
Siemens	0.0878	0.136	0.0670	-0.899***	-0.891***	-0.857***
	(0.326)	(0.327)	(0.328)	(0.292)	(0.302)	(0.295)
Meditec	-0.119	-0.126	-0.140	-0.423**	-0.587***	-0.401**
	(0.211)	(0.227)	(0.211)	(0.194)	(0.219)	(0.192)
Quadramed	1.404	1.377	1.312	0.803	0.760	0.895
	(0.874)	(0.863)	(0.869)	(0.752)	(0.747)	(0.750)
Others	-0.188	-0.287	-0.0891	-0.681**	-0.655**	-0.409
	(0.408)	(0.413)	(0.405)	(0.323)	(0.330)	(0.329)
N	13520	13520	13520	13470	13470	13470
P-value for joint significance	0.103	0.0641	0.0494	0.0000179	0.000829	0.00000148
P-value for joint equality	0.0875	0.0641	0.0435	0.000170	0.000829	0.0000123

Standard errors in parentheses

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

Figure 3: Pharmacy charge

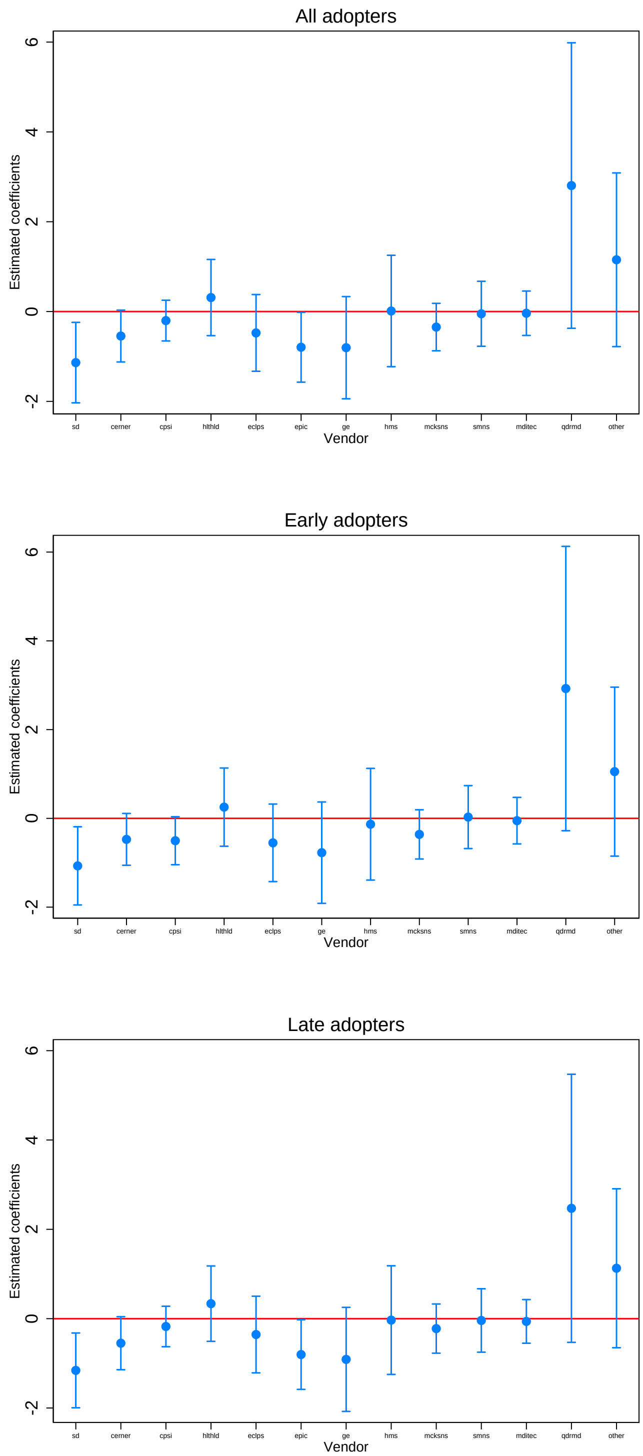


Figure 4: Radiology charge

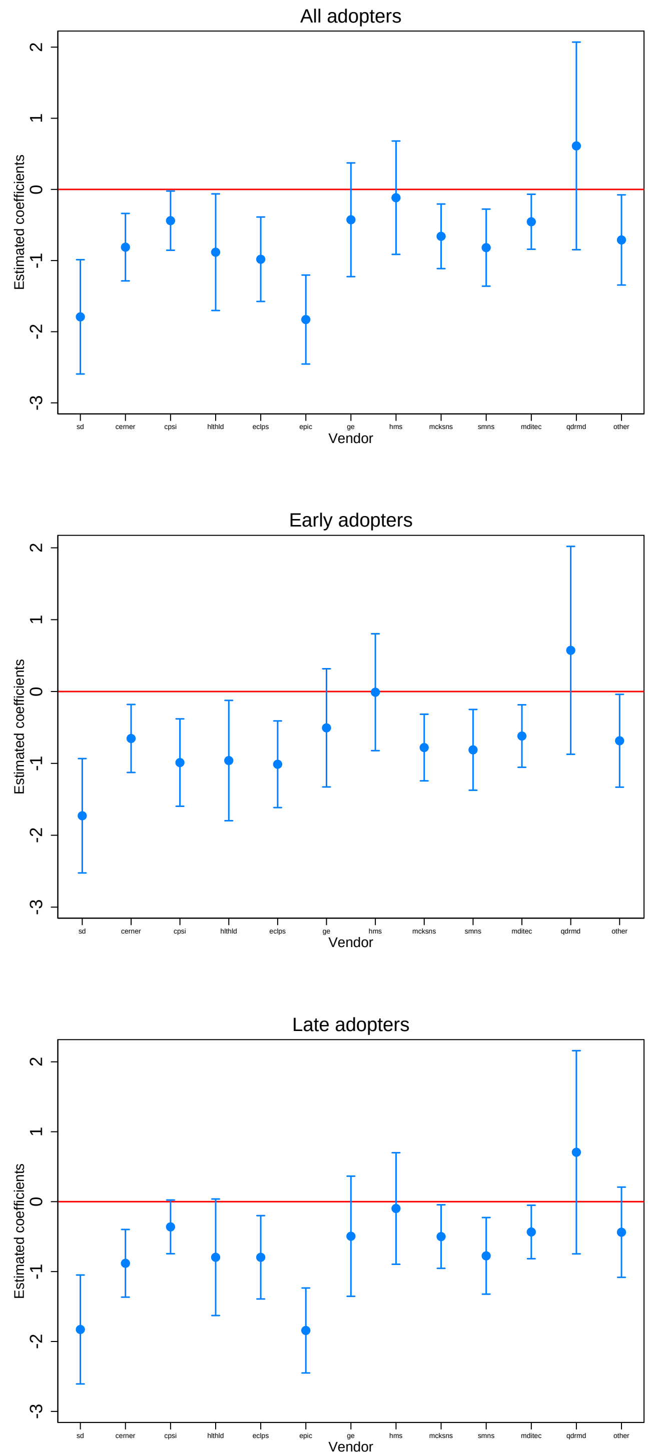


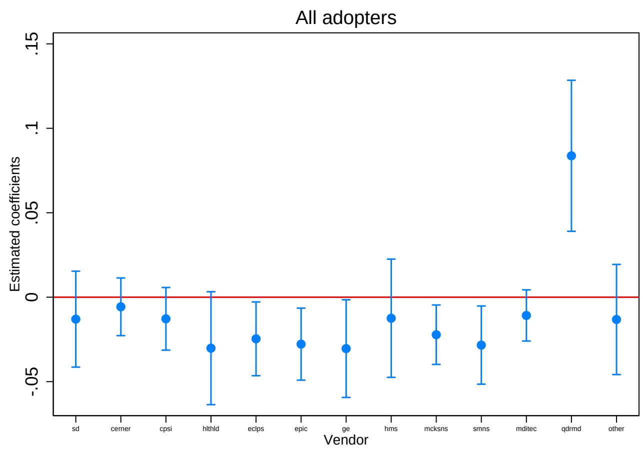
Table 10: Vendor-specific effects — 30-day mortality rate

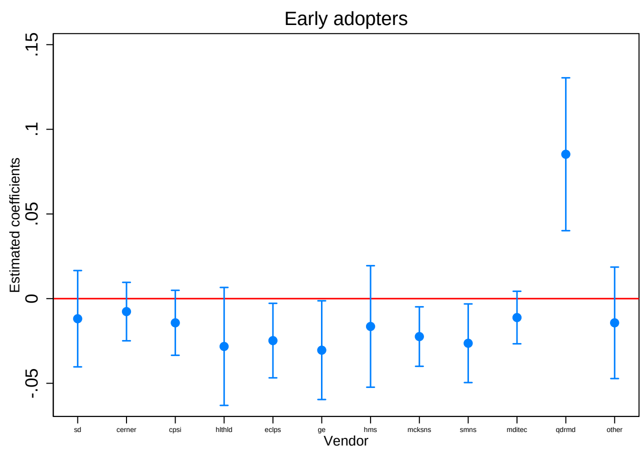
	No complexity adjustment			Patients admitted in the last 12 months			Patients NOT admitted in the last 12 months		
	General	Early	Late	General	Early	Late	General	Early	Late
Self-developed	-0.0130	-0.0119	-0.0233	-0.0306	-0.0278	-0.0495**	-0.0124	-0.0122	-0.0175
	(0.0145)	(0.0145)	(0.0147)	(0.0223)	(0.0224)	(0.0227)	(0.0156)	(0.0155)	(0.0158)
Cerner	-0.00568	-0.00765	-0.00494	-0.0201	-0.0222	-0.0181	-0.00313	-0.00553	-0.00225
	(0.00871)	(0.00880)	(0.00874)	(0.0155)	(0.0158)	(0.0156)	(0.00987)	(0.00989)	(0.00989)
CPSI	-0.0128	-0.0143	-0.0127	-0.00418	-0.00225	-0.00436	-0.0137	-0.0179*	-0.0134
	(0.00946)	(0.00978)	(0.00953)	(0.0192)	(0.0200)	(0.0195)	(0.00900)	(0.00985)	(0.00904)
Healthland	-0.0302*	-0.0282	-0.0291*	-0.0295	-0.0244	-0.0271	-0.0209	-0.0207	-0.0194
	(0.0170)	(0.0178)	(0.0171)	(0.0306)	(0.0318)	(0.0307)	(0.0210)	(0.0216)	(0.0210)
Eclipsys	-0.0246**	-0.0248**	-0.0215*	-0.0524***	-0.0522***	-0.0502***	-0.0163	-0.0164	-0.0117
	(0.0111)	(0.0112)	(0.0112)	(0.0183)	(0.0185)	(0.0185)	(0.0128)	(0.0129)	(0.0129)
Epic	-0.0278**	–	-0.0274**	-0.0364**	–	-0.0351*	-0.0362***	–	-0.0359***
	(0.0109)	–	(0.0109)	(0.0179)	–	(0.0180)	(0.0124)	–	(0.0124)
GE	-0.0304**	-0.0304**	-0.0257*	-0.0440*	-0.0411	-0.0467*	-0.0293*	-0.0312*	-0.0206
	(0.0148)	(0.0149)	(0.0152)	(0.0250)	(0.0255)	(0.0248)	(0.0167)	(0.0167)	(0.0170)
HMS	-0.0125	-0.0164	-0.0113	-0.0415	-0.0457	-0.0398	-0.00403	-0.00539	-0.00215
	(0.0179)	(0.0183)	(0.0179)	(0.0296)	(0.0301)	(0.0296)	(0.0207)	(0.0216)	(0.0208)
McKessons	-0.0222**	-0.0224**	-0.0203**	-0.0347**	-0.0346**	-0.0321**	-0.0210**	-0.0207**	-0.0190*
	(0.00898)	(0.00896)	(0.00907)	(0.0161)	(0.0161)	(0.0163)	(0.0100)	(0.0100)	(0.0100)
Siemens	-0.0284**	-0.0263**	-0.0280**	-0.0372*	-0.0370*	-0.0344*	-0.0317**	-0.0291**	-0.0327**
	(0.0118)	(0.0118)	(0.0118)	(0.0203)	(0.0204)	(0.0204)	(0.0133)	(0.0133)	(0.0134)
Meditec	-0.0108	-0.0112	-0.0102	-0.0175	-0.0164	-0.0171	-0.0114	-0.0132	-0.01000
	(0.00773)	(0.00791)	(0.00779)	(0.0141)	(0.0144)	(0.0143)	(0.00861)	(0.00871)	(0.00865)
Quadramed	0.0837***	0.0853***	0.0815***	0.0504	0.0514	0.0506	0.116***	0.119***	0.113***
	(0.0228)	(0.0230)	(0.0229)	(0.0470)	(0.0474)	(0.0471)	(0.0232)	(0.0233)	(0.0234)
Others	-0.0132	-0.0143	-0.0107	-0.0286	-0.0289	-0.0225	-0.0239	-0.0261	-0.0223
	(0.0166)	(0.0168)	(0.0167)	(0.0292)	(0.0292)	(0.0293)	(0.0171)	(0.0173)	(0.0173)
N	13547	13547	13547	12463	12463	12463	12460	12460	12460
P-value for joint significance	0.00254	0.00486	0.00848	0.170	0.234	0.186	0.0000578	0.0000440	0.000197
P-value for joint equality	0.00455	0.00486	0.0102	0.251	0.234	0.220	0.000106	0.0000440	0.000246

Standard errors in parentheses

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

Figure 5: Mortality rate (all patients)





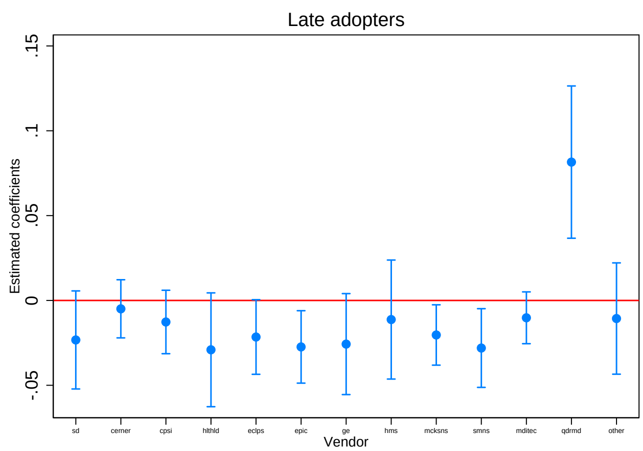


Figure 6: Mortality rate (severe patients)

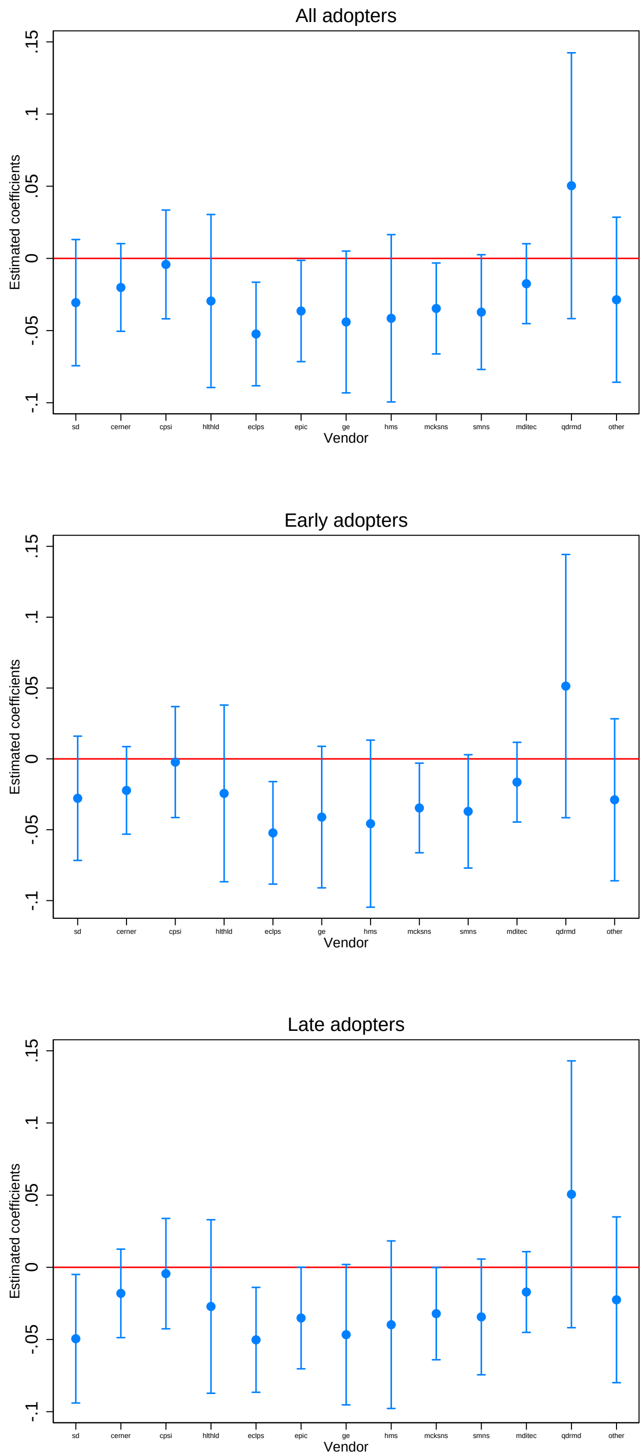


Figure 7: Mortality rate (less severe patients)

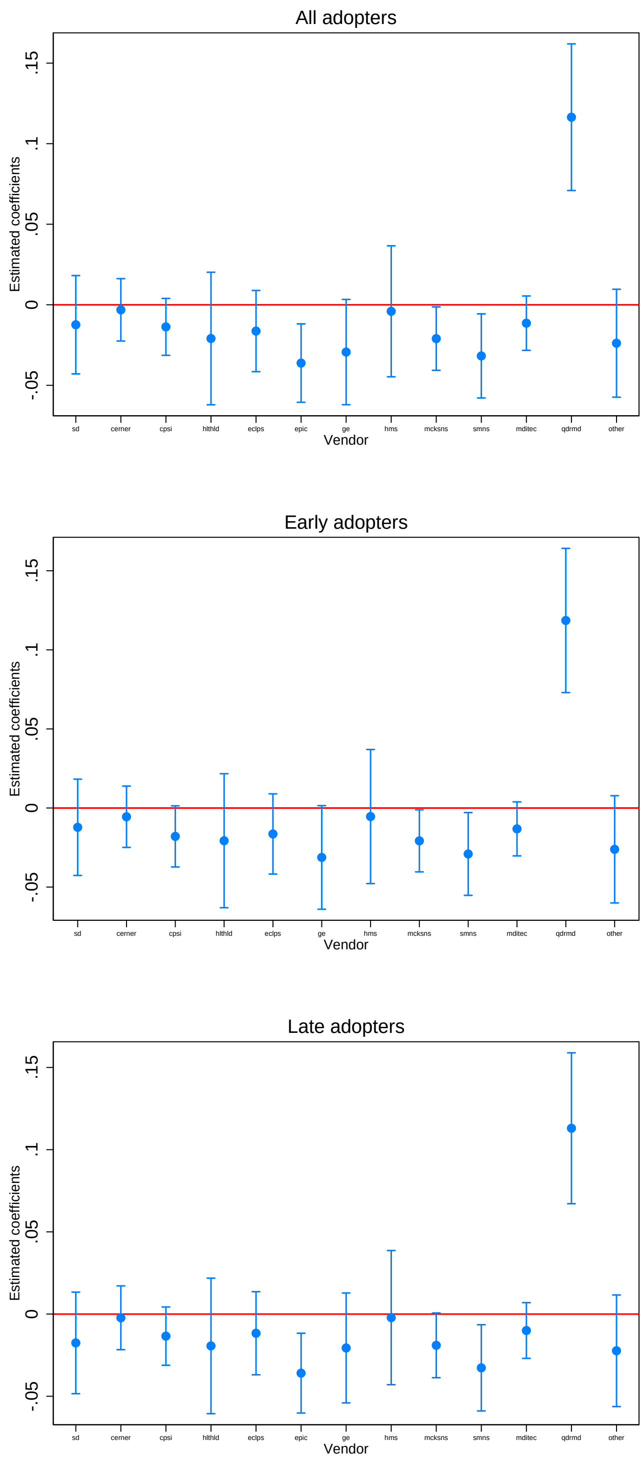


Table 11: Vendor-specific effects — Length of stay

	No complexity adjustment			Patients admitted in the last 12 months			Patients NOT admitted in the last 12 months		
	General	Early	Late	General	Early	Late	General	Early	Late
Self-developed	-0.0320	-0.0373	-0.121	-0.0319	-0.0358	-0.117	-0.0370	-0.0408	-0.122
	(0.138)	(0.136)	(0.135)	(0.142)	(0.141)	(0.140)	(0.142)	(0.141)	(0.139)
Cerner	0.0208	-0.0225	0.0330	-0.00294	-0.0346	0.00862	-0.00422	-0.0359	0.00736
	(0.0827)	(0.0845)	(0.0829)	(0.0872)	(0.0888)	(0.0877)	(0.0861)	(0.0878)	(0.0866)
CPSI	0.0932	0.0723	0.0971	0.100	0.0844	0.104	0.101	0.0846	0.104
	(0.0684)	(0.0716)	(0.0684)	(0.0697)	(0.0734)	(0.0699)	(0.0689)	(0.0725)	(0.0690)
Healthland	0.349**	0.319*	0.338**	0.307*	0.272	0.294*	0.310*	0.275	0.297*
	(0.169)	(0.186)	(0.169)	(0.174)	(0.190)	(0.174)	(0.173)	(0.189)	(0.173)
Eclipsys	0.0740	0.0677	0.0968	0.0768	0.0735	0.0965	0.0776	0.0744	0.0977
	(0.105)	(0.105)	(0.107)	(0.110)	(0.110)	(0.112)	(0.111)	(0.110)	(0.112)
Epic	0.00649	–	0.00583	-0.00450	–	-0.00550	-0.00635	–	-0.00736
	(0.113)	–	(0.113)	(0.117)	–	(0.117)	(0.117)	–	(0.116)
GE	-0.198	-0.196	-0.194	-0.169	-0.169	-0.164	-0.170	-0.170	-0.165
	(0.154)	(0.153)	(0.153)	(0.158)	(0.158)	(0.157)	(0.158)	(0.157)	(0.157)
HMS	0.286*	0.194	0.294*	0.325*	0.238	0.337*	0.323*	0.235	0.335*
	(0.167)	(0.168)	(0.166)	(0.177)	(0.178)	(0.177)	(0.176)	(0.177)	(0.175)
McKessons	0.0967	0.116	0.0682	0.0825	0.102	0.0564	0.0806	0.101	0.0544
	(0.0800)	(0.0805)	(0.0805)	(0.0830)	(0.0839)	(0.0837)	(0.0819)	(0.0828)	(0.0825)
Siemens	0.0267	0.0392	0.0143	0.0495	0.0584	0.0353	0.0536	0.0626	0.0394
	(0.122)	(0.122)	(0.123)	(0.125)	(0.125)	(0.126)	(0.125)	(0.125)	(0.126)
Meditec	0.114	0.119*	0.116*	0.104	0.102	0.110	0.102	0.100	0.109
	(0.0705)	(0.0720)	(0.0703)	(0.0728)	(0.0742)	(0.0728)	(0.0718)	(0.0733)	(0.0719)
Quadramed	0.541	0.553	0.541	0.473	0.484	0.475	0.463	0.473	0.465
	(0.342)	(0.340)	(0.339)	(0.350)	(0.348)	(0.348)	(0.347)	(0.345)	(0.344)
Others	0.121	0.104	0.106	0.116	0.0991	0.102	0.114	0.0962	0.0990
	(0.145)	(0.145)	(0.143)	(0.156)	(0.155)	(0.154)	(0.155)	(0.154)	(0.153)
N	13607	13607	13607	12470	12470	12470	12471	12471	12471
P-value for joint significance	0.140	0.211	0.279	0.132	0.292	0.279	0.132	0.291	0.274
P-value for joint equality	0.104	0.211	0.226	0.0965	0.292	0.223	0.0968	0.291	0.220

Standard errors in parentheses

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

Figure 8: Length of stay (all patients)

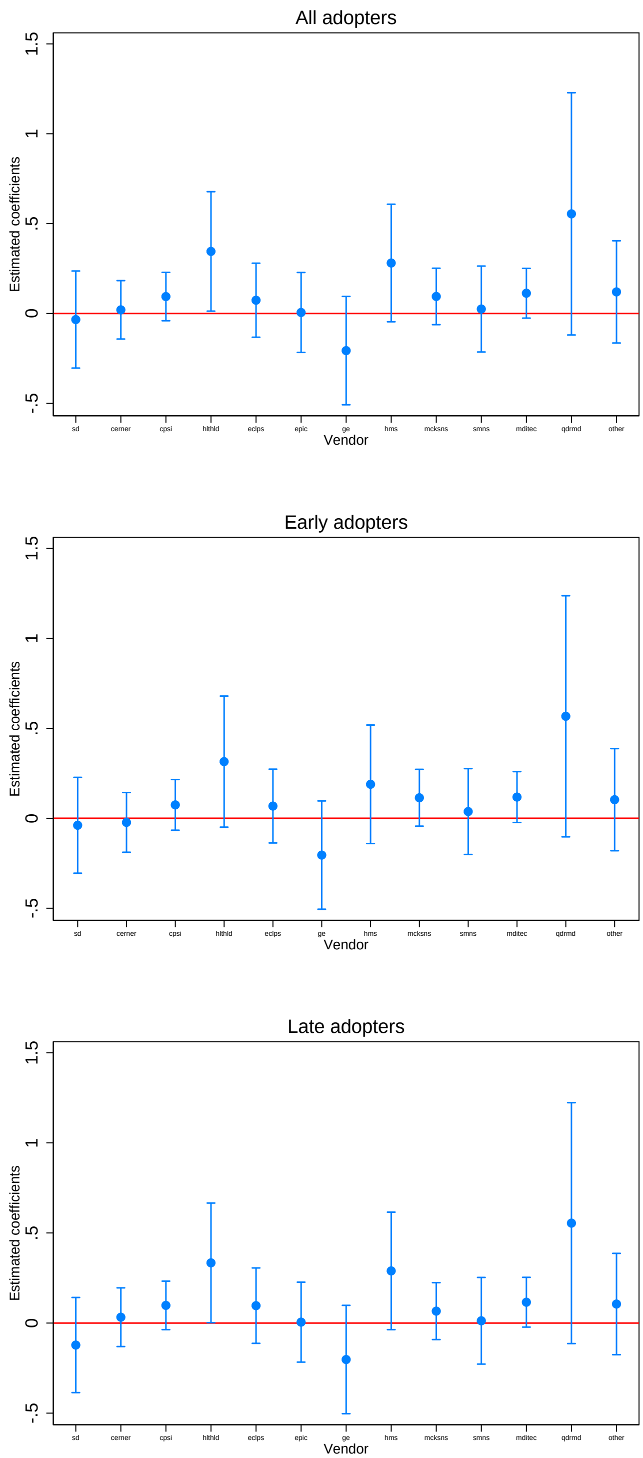


Figure 9: Length of stay (severe patients)

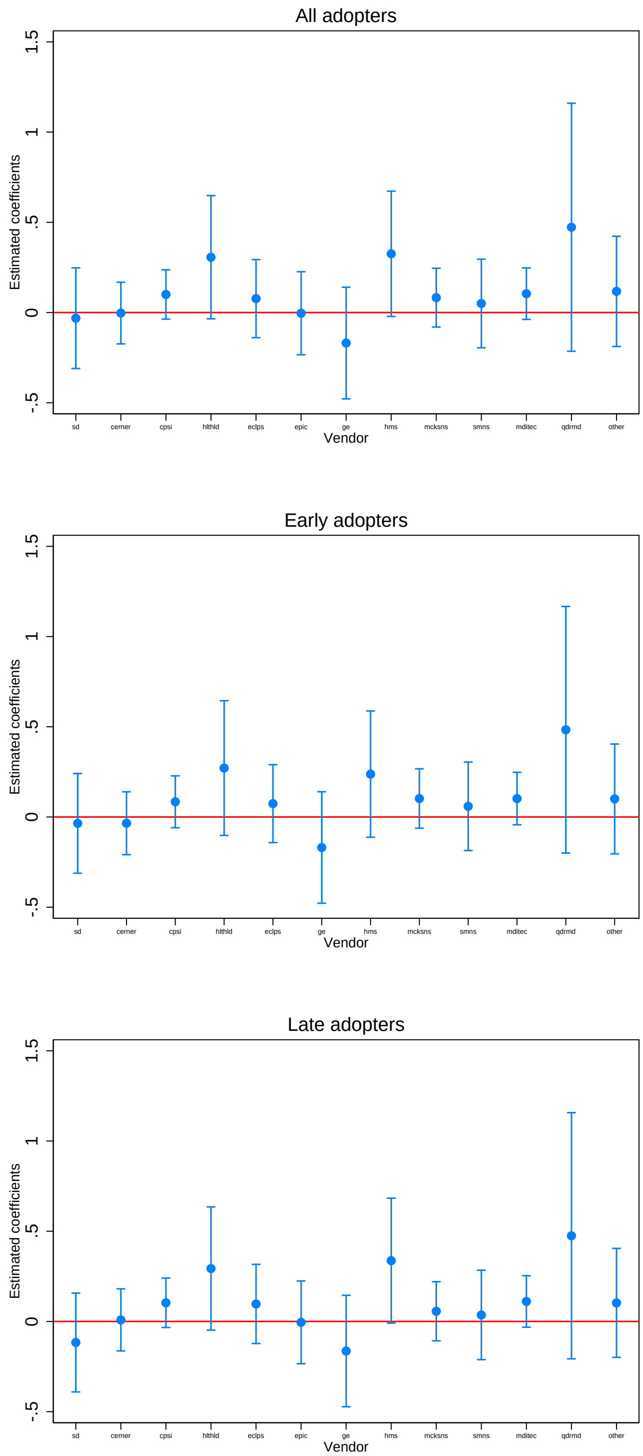
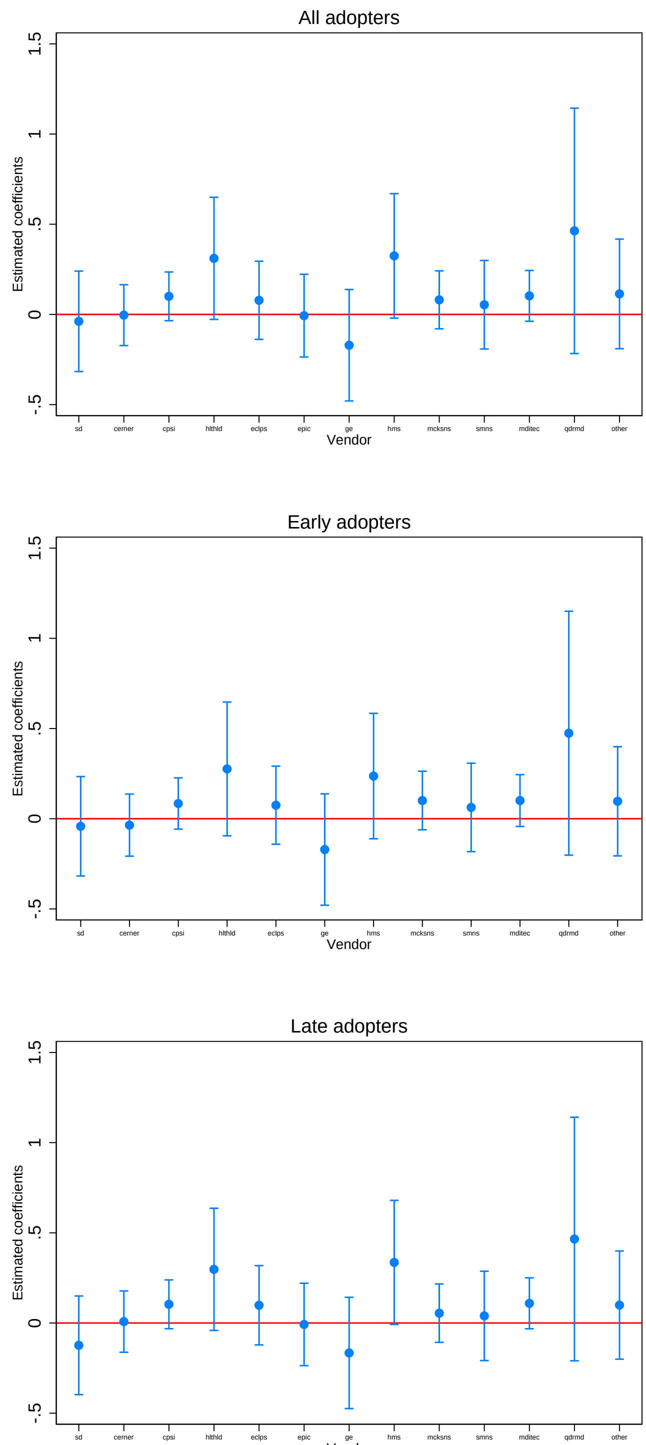


Figure 10: Length of stay (less severe patients)



Appendix I: For On-Line Publication Only

Table A1: First-stage results — multinomial logit regression

	Adoption choice
Market share	3.793***
	(0.304)
First leader	0.320***
	(0.0944)
Second leader	0.296***
	(0.0628)
Third leader	0.305***
	(0.0504)
Distance	-0.000192***
	(0.0000708)
Distance^2	4.23e-08*
	(2.21e-08)
log(revenue)	0.644***
	(0.0608)
R&D	3.77e-09***
	(3.53e-10)
R&D^2	-4.76e-19***
	(4.91e-20)
Marketing	2.71e-09***
	(3.48e-10)
Marketing^2	-1.10e-19***
	(1.41e-20)
N	190,498
F statistic	856.6

Standard errors in parentheses

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