The Effect of Electronic Medical Records on Hospital Utilization Costs

ABSTRACT: This paper examines the impact of adopting electronic medical record (EMR) systems on hospital utilization costs. We proxy for such costs using hospital charges (i.e., prices of services rendered) for Medicare diagnosis-related groups (DRGs), and hospitals' cost-to charge ratios (total Medicare allowable costs divided by total charges). Our sample is US hospitals, which exhibit considerable variation in the timing and extent of EMR adoption. We document a negative association between EMR adoption and both hospitals' DRG charges and cost-to-charge ratios, consistent with efficiency improvements stemming from higher quality of information supporting clinicians in patient care decision-making. Our results are robust to different EMR adoption measures, and various approaches to enhance identification including propensity score matching and a placebo test. Overall, our results indicate that EMR adoption is associated with reductions in healthcare expenditures, despite potential frictions such as high costs of adoption, maintenance, and integration.

Keywords: healthcare, hospitals, electronic medical records (EMRs), health information technology, healthcare costs, charges, payments.

Data: all data are obtained from the databases indicated in the paper

I. INTRODUCTION

From 1960 to 2020, U.S. health care expenditures increased from 5% to 18% of Gross Domestic Product. Annual health care spending in 2020 exceeded $4 trillion, making the U.S. system the most expensive in the world.[1] The dramatic scale and increase have brought substantial scrutiny, media attention, and regulatory provisions generating downward pressure on health care costs. As a result, both health care payers (including private health plans, as well as state and federal governments) and provider organizations (such as hospitals and health systems) continue to search for ways to reduce the high medical costs. Prior literature examines the role of electronic medical records (EMR) systems in controlling hospitals' medical expenditures and operating costs, with mixed evidence of their effectiveness (e.g., Agha 2014; Dranove et al. 2014). This paper adopts a novel approach by analyzing the effects of EMR adoption on hospital utilization costs: namely, hospital charges and cost-to-charge ratio.

Analyzing the effect of EMRs on hospital utilization costs is important as it helps to assess costs born by the health care ecosystem (patients, provider, and payers). Reducing hospital operational costs is only beneficial to lowering the cost of health care if the cost savings are passed on to patients and payers as lower charges (i.e., prices set by the hospital for each procedure) and ultimately as lower payments (i.e., the actual amounts hospitals receive from payers). EMRs are among the many advances in technology directly affecting the healthcare industry over the last several decades. EMRs vary in nature and are predominantly structured to track patient health, manage patient care across hospital services (e.g., surgery and physical therapy for a patient, who

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[1] See https://www.statista.com/topics/6701/health-expenditures-in-the-us/#dossierKeyfigures; http://www.insight-txcin.org/post/what-are-the-primary-drivers-of-healthcare-costs and https://www.statista.com/statistics/184968/us-health-expenditure-as-percent-of-gdp-since-1960/.

underwent a hip replacement), and bill payers and patients for services rendered. Thus, EMRs are not designed to directly support financial analyses for cost reduction or to improve efficiency in the hospital's operations. However, we posit that by improving the information environment in the hospital, EMRs support physicians in making patient care-delivery decisions that reduce waste and improve efficiency, thus lowering the costs associated with the utilization of hospital services for patients and payers.

We conduct our empirical analyses at the diagnosis-related-group (DRG) level, within hospitals and year.[2] DRGs comprise a classification of hospitalized patients based on their clinical diagnosis and the intensity of hospital resources needed to treat the patient.[3] Hospitals treating Medicare inpatients receive from the Centers for Medicare and Medicaid (CMS) a fixed amount set at the DRG level, independent of the actual cost they incur to treat the patient.[4] In contrast, hospitals record individual charges for *each* service rendered to the patient during their inpatient stay: these charges are akin to sticker prices for health care services (Reinhardt 2006). Thus,

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2 A diagnosis-related group corresponds to the classification of a patient based on diagnosis, treatment (including procedures performed by outside providers), and length of stay in the hospital. Factors determining the assignment of a particular DRG include the patient's demographic characteristics and comorbidities and complications. See https://hmsa.com/portal/provider/zav_pel.fh.DIA.650.htm (accessed July 13, 2021). In particular, we use the Medicare Severity DRG (MS-DRG) classification, which derives from a more recent and improved patient stratification methodology in use since prior to our sample period.

3 The intensity of resources needed relates to the severity of the illness, the presence of comorbidities or complications, and patient demographic characteristics (e.g., age, gender) that are clinically relevant for the definition of the patient's care cycle. Resource intensity refers to "length of stay, perioperative stay, operating room time, and use of ancillary services." Conditions included in a DRG must be clinically coherent, such that they refer to a common human organ system or etiology and care is provided by a common specialty. Finally, conditions must be consistent in terms of severity to the extent that greater severity correlates with greater consumption of hospital resources (e.g., appendicitis and peritonitis are not included in the same DRG because peritonitis, due to its higher degree of severity, consumes on average greater hospital resources). See Centers for Medicare and Medicaid Services, "Design and Development of Diagnosis Related Groups (DRG)," https://www.cms.gov/icd10m/version37-fullcode-cms/fullcode_cms/Design_and_development_of_the_Diagnosis_Related_Group_(DRGs).pdf, accessed May 30, 2022.

4 CMS uses an inpatient prospective payment system (IPPS). "The IPPS pays a flat rate based on the average charges across all hospitals for a specific diagnosis, regardless of whether that particular patient costs more or less. […] Payment also is adjusted for differences in area wage costs—and depending on the hospital and case—teaching status, high percentage of low-income patients, the use of new technology and extremely costly cases." See American Hospital Association, https://www.aha.org/inpatient-pps, accessed May 30, 2022.

following Eldenburg (1994), we use charges as a proxy for the utilization of hospital services to treat a patient classified in a particular DRG.[5] Care services performed (captured by the charges) vary across different patients within a DRG due to patient characteristics and physician preferences. Thus, the fixed nature of the DRG payments, coupled with the variation in case mix, translate into variation in hospital-level margins (captured by the cost-to-charge ratio).[6]

Our experimental variables capture hospital adoption of EMR systems. We use several proxies, all reflecting the implementation of five types of EMR systems: (1) clinical data repository (CDR), (2) clinical decision support system (CDSS), (3) computerized physician order entry (CPOE), (4) order entry (OE), and (5) physician documentation (PD) (see Appendix A). In particular, we use a proxy capturing full EMR adoption (that is, adoption of all five systems), a proxy for *partial* EMR adoption (whereby the hospital adopts *any* of the five individual EMR systems), as well as five alternative proxies for whether the hospital adopts each of the five individual EMR systems.

Empirical analyses support our prediction that EMR adoption is associated with lower average DRG charges and lower hospital-level cost-to-charge ratios. These negative associations can reflect hospitals reducing the charge amount and/or improving their efficiency in the delivery of patient care. We note that our examination of the relation between EMR adoption and hospitals' cost-to-charge-ratios suggests that an improvement in efficiency most likely explains our main

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[5] Federal regulations require hospitals to maintain a uniform chargemaster indicating the charge set for each service and procedure. However, payments do not correspond to these charges. Private insurance companies negotiate significantly lower prices for their members with large variation across health plans, geographies, and patient demographics. Medicare and Medicaid set prices at the national level that are often lower than the cost incurred by the hospital to provide the service. Self-insured patients are among the very few, who pay the amount indicated by the charge. See American Hospital Association, https://www.aha.org/system/files/2018-01/factsheet-hospital-billing-explained-9-2017.pdf, accessed May 30, 2022.

[6] Cost-to-charge ratios compare the Medicare-allowable costs of care provided with the charges associated with that care (Bai and Anderson 2015). These ratios can be calculated at the hospital level or at lower organizational levels within the hospital; our data comprises cost-to-charge ratio information at the hospital/year level.

results, as the results examining this ratio are consistent with costs (the numerator) reducing at a higher rate relative to charges (the denominator).

The above results are consistent across specifications using full EMR adoption, partial EMR adoption, and individual adoption of the five EMR systems. All analyses control for hospital characteristics (such as size and case complexity) and demographic characteristics of the area the hospital serves (such as employment and education), which have been found to affect our outcome variables. In addition, all analyses include an extensive fixed effects structure, controlling for hospital, year, and DRG to account for unobservable hospital, time, and DRG characteristics that may affect our outcome variables. Combined, these specifications lead to an effective within-hospital design. Thus, our results are consistent with a given hospital exhibiting reduced charges and cost-to-charge ratios relative to before its EMR adoption.

We confirm the robustness of our results using propensity score matching, wherein we match the treatment hospitals (those adopting EMRs) with the control hospitals (those not adopting EMRs) on all observable covariates in our analysis. Results are robust—and, in fact, stronger—relative to our main analyses. In addition, we conduct a placebo test, randomly assigning EMR adoption to hospitals. As expected, EMR adoption variables are insignificant, while the remaining control variables retain effects consistent with the main analyses. This suggests that the randomization decouples the effect of EMR adoption, and supports our primary inferences that EMR adoption leads to reduced health care utilization costs. Results also are robust to inflation-adjusting the dependent variables, and to controlling for hospital capital expenditures to ensure that our findings are not confounded by other concurrent investments being made.

Finally, we conduct three additional analyses. First, we assess the effects of EMR adoption on hospital payments (i.e., actual amounts received by hospitals from CMS, again assessed at the

DRG level). We provide consistent evidence that our EMR adoption proxies also are negatively associated with average hospital payments. This suggests that the efficiency improvements associated with the better information environment feed back to CMS as reduced resource utilization costs and lead to lower DRG payment amounts.[7] Second, we provide preliminary results that EMR adoption leads to improved service quality, reflected in reduced length of stays following EMR adoption. Finally, we confirm that our results are not confounded by state-level passage of price transparency regulation, the *Medicare Payment Rate Disclosure Act* of 2013.

Our paper provides three primary contributions. First, we offer evidence that EMR adoption decreases health care utilization costs. Prior accounting research finds that clinician access to cost information leads to lower operational costs and better resource allocations (Eldenburg 1994; Krishnan 2005; Eldenburg et al. 2010). We show that EMRs, which are not a natural source of cost information, contribute to healthcare cost reduction by supporting clinicians patient care decision-making, even in the absence of direct cost information. Most of the prior literature uses limited data sets to analyze variation in defined hospital operational costs (e.g., Agha 2014; Dranove et al. 2014) or focuses on how privately-insured contracts impact hospital prices (Cooper et al. 2019). We are the first to use a large and comprehensive national data set compiling hospital charges and cost-related information. Thus, we answer the call by Fichman, Kholi, and Krishnan (2011) to contribute to research examining the role of healthcare information technology on healthcare costs. Second, our evidence is consistent across multiple systems, suggesting that the negative effect of EMR adoption on hospital healthcare costs occurs broadly among a range of alternative systems. Critically, this further suggests that frictions such as

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[7] Hospitals serving Medicare patients must report their operating costs on an annual basis to CMS. See "Medicare Cost Report Electronic Filing (MCReF), https://www.cms.gov/Medicare/Compliance-and-Audits/Part-A-Cost-Report-Audit-and-Reimbursement/MCReF, accessed May 30, 2022.

implementation and integration costs appear to not outweigh the overall benefits of reduced costs through improved efficiency arising from improved information environments. Third, we confirm that average payments also appear to reduce subsequent to EMR adoption, suggesting the improved utilization costs impact actual payments made.

Section II presents the prior literature and hypothesis development. Section III describes the research design. Section IV discusses the sample and descriptive statistics, and Section V presents the primary empirical results. Section VI considers sensitivity analysis, and Section VII additional tests. Section VIII concludes.

II. PRIOR LITERATURE AND HYPOTHESIS DEVELOPMENT

In the past two decades, hospitals within the U.S. have moved toward adopting EMR systems, albeit at a slower than expected pace (see Ford et al. 2009 for a review). The Medical Records Institute (2005), in a national survey on the usage and trends of EMR systems across U.S. hospitals, finds only 27% of hospitals using one of the main EMR systems. Hillestad et al. (2005) suggests that the wide adoption of EMRs by hospitals could reduce annual health spending by $81 billion while improving the quality of care such as adverse drug events and chronic disease management.

The demand for accounting information in hospitals has increased in intensity as the health care industry has shifted from payment systems reimbursing hospitals for each procedure performed (i.e., fee-for-service) to a prospective payment system offering a fixed amount per diagnosis (i.e., DRG) (Krishnan 2005). Well-structured and implemented accounting information systems can help identify opportunities for cost reduction by detecting overtreatment (Eldenburg 1994) and resources waste (Eldenburg, Soderstrom, Willis, and Wu 2010). However, prior studies generally focus on the effects of implementing *cost-accounting* systems on cost performance (Eldenburg 1994; Krishnan 2005; Eldenburg et al 2010). In contrast, EMRs are *not* a natural source of cost-related information. EMRs are predominantly structured to facilitate the collection and aggregation of patient and treatment information, and to bill payers for services rendered. The proposed benefits to EMR adoption include improved diagnoses, reduced redundancies for procedures, better information-sharing across doctors and departments, and fewer errors. Thus, we posit that EMRs can nonetheless drive greater efficiency in health care delivery through greater support of clinical decisions and better coordination across professionals participating in the patient's care (Kim 1988).

EMR systems are costly to adopt and implement, requiring direct expenditures to cover acquisition of the systems from IT provider firms, customization to integrate with the hospital's existing systems and IT architecture, and training for both medical and administrative staff. In addition, such systems require continuous updating as medical procedures evolve, and ongoing improvements in worker skills (Bresnahan et al. 2002) as organizational decision rights evolve. The adoption of multiple EMR systems also can require considerable integration costs (for a review see Atasoy et al. 2019). Finally, information transfers across hospitals may lead to the sharing of proprietary information affecting the hospitals' competitiveness (Atasoy et al. 2018). Broadly, the potential benefits and costs of EMR adoption may vary depending on the nature of the hospital, the range of services and procedures provided, and characteristics of the geographic area in which the hospital operates.

Some research documents positive effects of EMR systems on hospital service quality (Buntin et al. 2011), such as reductions in medical errors and patient mortality (e.g., Tierney et al. 1990; Bardhan and Thouin 2013; Bates et al. 1998; Devaraj and Kohli 2000; Dexter et al. 2004;

McCullough et al. 2010; Miller and Tucker 2011; McCullough et al. 2016; Ransbotham et al. 2021). McCullough et al. (2016) finds that the adoption of EMR systems is beneficial for patients with more complex conditions among hospital providers within a hospital market (Wennberg et al. 2004; Huang et al. 2010; Lee et al. 2011).

Some studies document improvements in hospitals' financial performance associated with EMR adoption (e.g., Atasoy et al. 2018; Lee et al. 2013; Collum et al. 2016). Other research finds that the adoption of EMR systems is associated with disruptions in the business processes of hospitals, requiring workarounds (Soh and Sia 2004) that impose significant costs (Thakkar and Davis 2006). Moreover, prior research shows that hospitals face different barriers to adopting EMR systems, such as misalignment of costs and benefits or financial reimbursement (Hersh 2004; Bates 2005). Some hospitals still lack systems providing timely access to patient information and communicating health information to other providers, patients, and insurers. Some research fails to find that EMR adoption is associated with a significant improvement in the overall performance of hospitals (e.g., Dranove et al. 2014). Kellerman and Jones (2013) also fails to find evidence that EMR savings offset hospitals' adoption costs. Finally, while Agha (2014) and McCullough et al. (2010) document small benefits to EMR adoption, these studies find an increase in hospital medical expenditures. Combined, the evidence on the relationship between the EMR adoption and hospital operating costs is mixed.

While extensive research examines the influence of EMR adoption on hospital operational costs, it must be noted that any cost savings generated by improved operational efficiencies contribute to lowering the cost of healthcare only to the extent they are transferred to patients and payers through lower charges and payments. Theory argues that adoption of EMR systems can reduce hospital-generated healthcare costs through two channels. First, EMR systems can increase the ability to inform and direct clinician behavior, leading to more standardized procedures, reducing unnecessary tests and duplicate exams, and thus generating more informed decision making (e.g., Kim and Lee 2020). Collectively, these effects should reduce the costs of achieving similar healthcare outcomes through improved efficiencies. Second, EMR systems can increase information transparency by enabling hospitals to communicate and exchange information with other providers (e.g., Goldschmidt 2005; Atasoy et al. 2018). Enhanced transparency and information sharing across participants can increase coordination throughout the patient's cycle of care and best practice sharing. This can occur either within a health care provider organization (e.g., across clinical departments within a hospital) or across providers (e.g., between a hospital and a skilled nursing facility). Combined, these mechanisms should lead to reduced utilization of health care services (especially if unnecessary or duplicated) in the patient care plan. Fewer services performed should in turn be reflected in lower DRG-level hospital charges.[8, 9] We formalize our prediction in Hypothesis 1.

HYPOTHESIS 1. *Electronic medical records adoption is associated with subsequent lower DRG-level hospital charges.*

Whether reduced charges at the DRG level reflect greater operational efficiency or simply a response to pressures from competitors, regulators, and the public to lower prices is an empirical question. Historically, hospitals collect amounts corresponding to their charges in a very small number of cases, such as self-insured patients, out-of-network patients, auto insurers and casualty insurers, which combined comprise less than 15% of patients for an average U.S. hospital (Bai and Anderson 2016). Research documents that "hospitals have sole discretion in determining their

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[8] Recall that hospitals post charges for every service rendered to the Medicare patient, but receive a lump-sum payment from CMS corresponding to the DRG.

[9] Charges in healthcare correspond to the hospital's sticker price for a particular procedure or treatment. The amounts appear on medical bills and correspond to the price paid by uninsured patients. Insured patients pay a portion of the charges or a copay, depending on their health insurance arrangements.

chargemaster prices and there is a lack of rigorous methodology for constructing those prices" (Bai and Anderson 2016, p. 1658). With CMS's move to prospective payment systems in the 1980s, under which CMS pays set prices for each DRG, and with private insurers negotiating prices directly with each hospital, the relevance of chargemaster prices has decreased significantly, resulting in hospitals facing very weak incentives to reduce their chargemaster prices (Bai and Anderson 2015, 2016).[10]

However, hospitals periodically calculate and report to CMS their cost-to-charge ratio (CCR), representing the total Medicare allowable costs[11] as a proportion of all charges posted for Medicare patients. If charges for individual procedures and supplies are not subject to material changes from year to year, but the efficiency of care delivery improves, we should observe a faster reduction in total costs (i.e., the numerator) compared to total charges (i.e., the denominator), and thus a reduction of the CCR. Accordingly, we predict the following.

HYPOTHESIS 2. *Electronic medical records adoption is associated with subsequent lower cost-to-charge ratios.*

III. RESEARCH DESIGN

We examine the effects of EMR adoption on hospital charges for diagnosis-related group (DRG) procedures using the following specification:

$$ln(Y)_{dht} = \beta_1 EMR_{ht} + \beta_2 Controls\_Hospital_{ht} + \beta_2 Controls\_MSA_{mt} + \alpha_d + \gamma_h + \theta_t + \varepsilon_{dht}. \quad (1)$$

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[10] In 2013, a regulatory provision was introduced to require annual disclosure of health care charges. The provision was never converted into law, however it remained in existence as a CMS policy. As discussed later in the sensitivity analyses, we confirm that the introduction of this regulatory provision does not affect our results.

[11] These are costs that pertain to the treatment of Medicare patients.

We first estimate equation (1) where the dependent variable $ln(Y)_{dht}$ is *ln*(*Average Charges*), defined as the log of the average charge for services covered by Medicare for all discharges at the DRG level d for hospital h and year t (i.e., the unit of analysis is the DRG-hospital-year level). Second, we estimate equation (1) where the dependent variable is *ln*(*Cost-Charge Ratio*), defined as the log of the hospital's cost-to-charge ratio (CCR). The CCR is measured as the total Medicare allowable costs reported by the hospital in year *t*, divided by the total charges reported by the hospital Medicare patients across all DRGs. We log transform the dependent variables to reduce the impact of skewness on the results.

The experimental variable EMR_{ht} is for whether hospital h adopts an EMR system in year t. We use several alternative proxies, all of which are derived based on five EMR systems. First, the clinical depository system (CDR) is a database used to maintain up-to-date records of patients. Second, the clinical decision support system (CDSS) is a database that assists practitioners with diagnosis and treatment plans. It takes data from other systems to better diagnose patients and check for medical errors. Third, the computerized physician order entry system (CPOE) is a database allowing physicians to enter, store, and share patient data and diagnoses, as well as electronically issue medical orders. Fourth, the order entry system (OE) is a database that lets hospitals replace paper forms with electronic records. Fifth, the physician documentation system (PD) is a database allowing physicians to maintain electronic records about patients' conditions.

Using these five systems, we derive seven proxies for EMR adoption. Our first proxy is *EMR_All*, an indicator variable equal to one if hospital *h* has adopted all five EMR systems as of year *t*, and zero otherwise. Our second proxy is *EMR_Partial*, an indicator variable equal to one if hospital *h* has adopted at least one EMR system as of year *t*, and zero otherwise. Our third through seventh proxies alternatively assess each of the five individual EMR systems: *EMR_CDR* (clinical data repository), *EMR_CDSS* (clinical decision support system), *EMR_CPOE* (computerized practitioner order entry), *EMR_OE* (order entry), and *EMR_PD* (physician documentation). Each proxy is defined as an indicator variable equal to one if hospital *h* has adopted the CDR, CDSS, CPOE, OE, or PD system, respectively as of year *t*, and zero otherwise. Across all specifications, β_1 is our coefficient of interest. The predicted sign is negative, indicating that the EMR adoption is associated with lower hospital utilization costs as proxied via charges for Hypothesis 1, and via cost-to-charge ratio for Hypothesis 2.[12]

The model includes two sets of control variables. The first group ($Controls\_Hospital_{ht}$) controls for time-varying hospital characteristics. We include the number of discharges billed by the provider for inpatient hospital services (*Discharge*) to proxy for the volume of activity of the hospital. We use, as an indication of the size of the provider organization, the number of licensed beds (*Beds*). We use the number of intensive care beds (*IC_Beds*) to control for characteristics of the hospital operations that could be associated with health care utilization costs. All three variables reflect elements of a hospital's economies of scale, with predicted negative coefficients for each. We include the case mix index (*CMI*) to capture the hospital's average disease severity (Mendez et al. 2014) and complexity of all patient's diagnoses, and thus can influence health care utilization costs. More complexity can reflect sicker patients (Ganju et al. 2020) and thus higher charges and higher cost-to-charge ratios, suggesting a predicted positive coefficient. Farley and

[12] Because the decision to adopt an EMR system (or set of EMR systems) may be endogenous, we conduct the following predictive analyses. We define our outcome variable to be the choice for a hospital to adopt an EMR system in a particular year; we alternatively measure the outcome as adoption of all systems (i.e., *EMR_All*), as adoption of any system (i.e., *EMR_Partial*), or as adoption of a specific individual system among the five we examine. We use as the determinants all of the control variables indicated in Equation (1). Untabulated results fail to find evidence that any of the included controls attains significance in the decision to adopt these EMR systems in whole or in part. Of note, this suggests that other idiosyncratic factors likely drive the EMR adoption system, and mitigates concerns that EMR adoption is endogenous and driven by other factors (such as hospital size) within our model. Further, we note that it is unlikely that reverse causality (i.e., that charges drive adoption of EMR systems) is occurring. Finally, later we discuss sensitivity analyses (including propensity score matching and placebo tests) estimated to enhance identification.

Hogan (1990) documents that case mix specialization across hospitals can reduce hospital costs. We follow Atasoy et al. (2018) and control for possible spillover effects by including the average EMR adoption of other hospitals in the same Hospital Service Area (HSA), excluding the focal hospital (EMR_HSA). To the extent that EMR adoption by peer hospitals in a geographic area similarly leads to reduced health care utilization costs, the predicted sign is negative.

The second group of control variables ($Controls\_MSA_{mt}$) reflects various characteristics of the hospital's metropolitan statistical area (MSA) *m* for year *t*. Demographic and socioeconomic characteristics of the patient population served by the hospital are likely to correlate with the average severity and complexity of cases and, thus affect hospital utilization costs.[13] Thus, we include the unemployment rate (*Unemployment*), the mean household income (*Income*), and the percentage of the population having a bachelor's degree or higher (*Education*) as proxies for the economics of the MSA. We also use three measures of demographic characteristics of the MSA: the log of total population (*Population*), the ratio of males per 100 females (*Sex_Ratio*), and the ratio of population under 18 plus that over 65 divided by the population age 18–64 (*Age_Ratio*). The last ratio reflects the skew in MSA toward populations more likely to require (more expensive) medical procedures.

Finally, the model includes three levels of fixed effects: for DRG (α_d) to control for time-invariant factors specific to diagnosis-related groups; for hospital (γ_h) to control for time-invariant unobservable factors specific to an individual hospital; and for year (θ_t) to control for time-specific temporal trends shocks. Analyses estimated using hospital charges as the dependent variable include fixed effects at the DRG, hospital, and year level; those estimated using hospital cost-to-

[13] In fact, CMS explicitly adjusts its payment rates based on the statistical characteristics of the local area served.

charge ratios as the dependent variable include fixed effects at the hospital and year level. All analyses use robust standard errors clustered by hospital and year.

IV. SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

We construct a hospital-level panel data set from 2011 to 2015 to examine the effects of EMR adoption on hospital DRG charges. Our data come from four sources. First, we collect providers' EMR adoption information from the Healthcare Information and Management Science Society (HIMSS) data set, which contains hospital-level information about the timing and type of different EMR systems adopted by a given hospital. As previously discussed, the five individual EMR systems we consider are clinical data repository, clinical decision support system, computerized physician order entry, order entry, and physician documentation. Second, we obtain from the American Hospital Association data on inpatient charges for 100 common procedures (i.e., DRGs), as well as hospital-level cost-to-charge ratios. Third, we obtain hospital characteristics (e.g., number of beds, readmission rate, etc.) from the Medicare Inpatient and Prospective Payment System (IPPS) files. Fourth, we secure hospital demographic and geographic information from the U.S. Census. Table 1 summarizes our sample selection, which contains 147,318 observations at the DRG-hospital-year level, spanning 1,457 individual hospitals for 2011 to 2015.

[Insert Table 1 near here]

Table 2 presents the descriptive statistics for our sample. The mean value of the first dependent variable, *ln*(*Average Charges*), is 10.548 (untransformed variable of *Average Charges* mean is $53,105). *ln*(*Cost-Charge Ratio*) exhibits a mean of 0.220. Our main experimental variable, *EMR_All*, has a mean of 0.616, indicating that 61.6% of the hospital-years reflect adoption of all five EMR systems during our sample period. *EMR_Partial* has a mean of 0.917, reflecting that 91.7% of hospital-years reflect adoption of at least one EMR system during our sample period. The three most commonly adopted EMR systems are the clinical decision support system (*EMR_CDSS*, mean = 90%), order entry system (*EMR_OE*, mean = 89.9%), and clinical data repository (*EMR_CDR*, mean = 89.4%). The hospital operation variables (e.g., *Discharge*, *Beds*, *IC_Beds*) exhibit considerable variation across our sample as evidenced by the large standard deviation in each variable, as do the MSA variables (e.g., *Education*, *Age_Ratio*). Table 3 presents the correlations.

[Insert Tables 2 and Table 3 near here]

V. EMPIRICAL RESULTS

Primary Analyses

Table 4 summarizes our primary empirical results. Columns (1) and (2) present the estimation results of equation (1) at the DRG/hospital/year level using *ln*(*Average Charges*) as the dependent variable. The coefficient for full adoption of all EMR systems is negative but insignificant (*EMR_All* = –0.008, *t*-stat = –1.121). The coefficient for partial adoption of any EMR system is significantly negative (*EMR_Partial* = –0.040, *t*-stat = –3.884, corresponding to a 3.92% decline in average DRG charges). As these analyses include hospital fixed effects, our results should be interpreted as within-hospital estimations. Thus, hospitals exhibit lower average DRG charges after the adoption of any of the five individual EMR systems (i.e., partial adoption) relative to before adopting that system, as well as to hospitals that have not adopted any EMR system. This provides evidence in support of Hypothesis 1.

Columns (3) and (4) present results using the dependent variable *ln*(*Cost-Charge Ratio*). The coefficient on *EMR_All* is significantly negative (–0.012, *t*-stat = –3.270, corresponding to a

1.19% decline) and on *EMR_Partial* is insignificant (0.008, *t*-stat = 0.878). These results provide complementary insights to those above regarding average charges, by confirming that the cost-to-charge ratio declines coincident with EMR adoption. In particular, this suggests that Medicare allowable costs incurred by the hospital (i.e., the numerator) decline at a faster rate relative to the total charges posted for Medicare patients (i.e., the denominator). This also provides evidence in support of Hypothesis 2.[14]

The control variable coefficients are generally consistent with our expectations, though significance varies considerably depending on the specification. Note that the extensive fixed effect structure (DRG, hospital, and year) likely subsumes much of the explanatory power of the control variables. Consistent with this notion, untabulated estimations excluding hospital fixed effects confirm that the hospital-level control variables generally attain the predicted signs.

Overall, our results suggest that full or partial adoption of EMR systems lead to lower average charges and lower average cost-to-charge ratios. Thus, we find evidence consistent with adoption of EMR systems leading to lower health care utilization costs.

[Insert Table 4 near here]

Individual Electronic Medical Record Systems

We next decompose EMR adoption into each of the five constituent systems (see Appendix A). For each system, we estimate equation (1) replacing the experimental variable with an indicator variable equal to one if hospital *h* has adopted the specific EMR system in year *t*, and

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[14] We also examine an alternative dependent variable of *EMR_NumSystems*, defined as the number of EMR systems that hospital *h* has adopted as of year *t*. This provides a more continuous measure capturing the extent to which the hospital has adopted EMR systems, relative to our binary *EMR_Partial* variable. Untabulated results reveal that both *ln*(*Average Charges*) and *ln*(*Cost-Charge Ratio*) exhibit significantly negative associations with *EMR_NumSystems*, consistent with our primary results.

zero otherwise. This enables us to examine whether the effects we document in our main analysis above reflect any particular EMR system or are broadly reflective of EMR adoption.

Table 5 presents the results. Panel A reports the coefficients estimated for equation (1) when the dependent variable is *ln*(*Average Charges*). The results reveal significantly negative coefficients for our treatment variable consistent across all five individual systems. Specifically, we document a significantly negative coefficient on *EMR_CDR* in Column (1) (–0.034, *t*-stat = –3.846, corresponding to a 3.34% decline in average charges), *EMR_CDSS* in Column (2) (–0.033, *t*-stat = –3.537, a 3.25% decline), *EMR_CPOE* in Column (3) (–0.020, *t*-stat = –2.837, a 1.98% decline), *EMR_OE* in Column (4) (–0.033, *t*-stat = –3.419, a 3.25% decline), and *EMR_PD* in Column (5) (–0.016, *t*-stat = –2.316, a 1.59% decline). Untabulated effects of the control variables are consistent with those reported in Table 4. These results suggest that adoption of any of the five individual EMR system leads to reduced medical charges; restated, the results indicate that this effect does not appear limited to any individual or subset of these systems.

Panel B presents results using the dependent variable *ln*(*Cost-Charge Ratio*). We find significantly negative coefficients in two of the five individual systems: *EMR_CPOE* in Column (3) (–0.014, *t*-stat = –3.843, corresponding to a 1.39% decline), and *EMR_PD* in Column (5) (–0.009, *t*-stat = –2.169, a 0.90% decline). Thus, we find evidence that adoption of individual EMR systems leads to reduced average cost-charge ratios. We note that CPOE systems support communication and coordination across hospital departments (e.g., between the prescribing physician and the diagnostic laboratory), while PD systems support patient-care decisions by allowing physicians to maintain a complete clinical profile inclusive of extant conditions affecting the patient. While the former likely fosters greater operational efficiencies across clinical departments, the latter likely supports improved and more comprehensive care plans.

Overall, the results reflect a reduction in hospital charges (cost-charge ratio) coincident with the adoption of any of the five EMR systems (with the adoption of CPOE and PD systems).[15]

[Insert Table 5 near here]

VI. SENSITIVITY ANALYSES

Propensity Score Matching

We next use propensity score matching to enhance identification of our research design. This technique provides more robust causality between our treatment (EMR adoption) and outcome (decreased hospital utilization costs) by matching treatment hospitals (EMR adopters) with control hospitals (non-EMR adopters) on observable characteristics. This helps to confirm that any incremental decline in hospital utilization for the treatment group, relative to otherwise identical hospitals, is attributable to the EMR adoption. Thus, the matching mitigates the potential effects of other covariates driving observed differences between the treatment and control groups. The limitation of this approach is that the matching occurs only on observable characteristics.

Table 6 Panel A presents the treatment and control samples before and after matching. Column (3) shows that 5 of 11 covariates exhibit significant differences across the treatment and unmatched control groups. We then match on all covariates, representing the full set of control variables from equation (1). Column (5) reveals a decline in significant differences to only one of eleven covariates (only the difference for *EMR_HSA* remains significant, though considerably reduced relative to before matching). This suggests that the matching substantially reduces differences across the treatment and control groups among the covariates.

[15] Note that results of both panels are unchanged to winsorizing all variables at the 1% level. Results also are robust to including the lagged value of the dependent variable (i.e., an AR(1) model) to account for serial correlation. We use this latter specification to rule out that other factors (not captured in the control variables of Equation (1)), which may affect our findings. Of note, we fail to find any evidence of increases in the cost-charge ratio, suggesting that margins are not decreasing, and consistent with the efficiency story.

Panel B presents the results of the replicated multivariate analyses using the propensity score matched sample for the dependent variable of *ln*(*Average Charges*). All regressions include the same control variables (untabulated) and fixed effects as the primary analyses of Tables 4 and 5. The sample size is reduced relative to the primary analyses due to the matching (*N* = 85,507). Columns (1)–(2) present results using the aggregate EMR adoption variables *EMR_All* and *EMR_Partial*, respectively. Across both columns, the estimated coefficients are significantly negative, consistent with the prior results. Columns (3)–(7) then present results using the indicator variable for each of the five individual EMR systems (i.e., *EMR_CDR*, *EMR_CDSS*, *EMR_CPOE*, *EMR_OE*, and *EMR_PD*). The coefficients associated with the experimental variables again remain significantly negative across all five specifications. Panel C presents similar results using the dependent variable *ln*(*Cost-Charge Ratio*) (*N* = 3,161). Again, we find significantly negative effects for *EMR_All* and for *EMR_CPOE* system; the remaining coefficients are insignificant.

Overall, our findings appear robust to using a propensity score matched sample. This suggests that systematic differences in the other covariates are unlikely an alternative explanation for our findings.

[Insert Table 6 near here]

Placebo Tests

Next, we use a placebo test to ensure that our results reflect the adoption of EMR systems, as opposed to potential pre-existing trends in charges and margins associated with industry-wide pressures to reduce healthcare costs. We assign each hospital to a random EMR adoption date. If our primary regressions reflect a general trend in EMR adoption, the randomization will continue to document the negative association between (randomized) EMR adoption and hospital utilization costs. If randomization decouples the economic link between actual EMR adoption and its effect on hospital utilization, then we expect to find insignificant coefficients associated with our experimental variable under these placebo tests. This latter scenario would provide evidence supporting identification within our primary analyses. Restated, such findings would be consistent with EMR adoption leading to reductions in hospital utilization costs. Thus, we repeat all the estimations of equation (1) previously described, except the experimental variables (*EMR_All*, *EMR_Partial*, *EMR_CDR*, *EMR_CDSS*, *EMR_CPOE*, *EMR_OE*, and *EMR_PD*) now reflect hospital *h* being *randomly* assigned to year *t* for its adoption of all or some individual EMR system. We conduct the randomization across 1,000 trials for each EMR experimental variable and present average coefficients and *t*-statistics across the trials.

Table 7 presents the results. Panel A documents results with *ln*(*Average Charges*) as the dependent variable. Columns (1) and (2) present results using *EMR_All* and *EMR_Partial* as the experimental variable, respectively; Columns (3)–(7) present those using each of the individual systems. Across all columns, we fail to find significance on the coefficients for any of the EMR variables. We tabulate the control variables in this analysis to confirm that the coefficients on the control variables are unaffected by the randomization. We continue to find unchanged significance on the control variables as documented in Table 4. That is, the control variables shown as significant in Table 4 remain significant in this placebo test, thus confirming that the randomization decouples the treatment effect of EMR adoption, but not the control effects in the other variables.

Panel B presents results using *ln*(*Cost-Charge Ratio*) as the dependent variable. As above, none of the coefficients on the EMR variables is significant. Results on the significant control variables from Table 4 again remain unchanged, consistent with the randomization affecting only the association between EMR adoption and hospital utilization.

Overall, the evidence is consistent with the randomization of EMR adoption date breaking the economic link between EMR adoption and hospital utilization costs. That is, the results from these placebo tests are consistent with our primary regressions finding an association between EMR adoption and reductions in health care utilization costs.

[Insert Table 7 near here]

Alternative Dependent and Control Variables

Next, we examine an alternative dependent variable by inflation-adjusting *ln*(*Average Charges*). Our primary analyses use unadjusted amounts, which provide a conservative estimate of the effect of EMR adoption on health care utilization costs by not reflecting increases in average hospital charges that occur over time due to inflation. Untabulated results using inflation-adjusted dependent variables are similar—and, in fact, stronger—relative to those presented in Tables 4 and 5. In particular, we again find decreased (inflation-adjusted) average charges for partial EMR adoption and each of the individual EMR systems. The effect for full EMR adoption is again negative but insignificant.

As a final sensitivity analysis, we include additional controls to address concurrent investments hospitals may make in other assets. Other investments besides EMR system adoption (such as in medical equipment or facilities) could drive declines in hospital charges such as through enhanced efficiencies. We note that such investment would need to coincide with the hospital-specific temporal adoption of the EMR systems we examine; the time-varying adoption of EMR systems that we observe suggests that this alternative explanation is less likely. Nonetheless, we reestimate the Table 4 and Table 5 regressions, now including measures controlling for the hospital's investment in fixed assets. Untabulated results are unchanged for either charges or the cost-to-charge ratio. This suggests that other investments are not an alternative explanation for our findings.

VII. ADDITIONAL ANALYSES

The Effect of Electronic Medical Record Adoption on Hospital Payments

We now examine the effect of EMR adoption on an alternative outcome variable: hospital payments. Ultimately, efficiencies in the healthcare system obtained via improved hospital utilization should reflect reduced payments. That is, greater efficiency (such as through reduced redundancies in testing) should ultimately lead to reduced average payments at the DRG level from Medicare. Accordingly, we now use the dependent variable of the hospital's average payments *ln*(*Average Payment*), defined as the log of the average of Medicare payments for the DRG.[16]

From Table 2, descriptive statistics for *ln*(*Average Payments*) reflects a mean of 9.186 (untransformed of $12,442); as expected, this latter amount is significantly lower relative to the previously reported average charges ($53,105). Table 8 presents the regressions results. In Panel A, we first present results replicating the primary analyses of *EMR_All* and *EMR_Partial* (i.e., Table 4) as well as for the individual EMR systems (i.e., Table 5). We find a significantly negative coefficient on *EMR_All* in Column (1) (–0.010, *t*-stat = –3.259, corresponding to a 0.10% reduction in payments), and on *EMR_Partial* in Column (2) (–0.013, *t*-stat = –2.752, a 1.29% decline). In addition, we find consistently negative coefficients for all five of the individual EMR systems in

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[16] DRG payment rates are unilaterally defined by the Centers for Medicare and Medicaid Services (CMS) and are revised annually. These amounts are prospectively defined (i.e., they are not based on actual costs reported by the hospital) and are based on large sample averages and a number of adjustments such as for local labor markets, type of hospital, and demographic characteristics of the patient population. The DRG-related payment amounts are intended to cover the costs that hospitals incur on average for labor and nonlabor resources (i.e., materials and overhead costs) used in the treatment of a specific condition for a specific type of patient (i.e., severity of the illness, comorbidities, complications, etc.). Additional amounts may accrue if the provider organization is a teaching hospital, it treats a high percentage of low-income cases, or it represents a high-cost outlier cases. See https://www.ahd.com/AcutePaymtSysfctsht_JAN09.pdf (accessed on July 13, 2021).

Columns (3)-(7). Specifically, we find significantly negative coefficients on *EMR_CDR* in Column (3) (–0.014, *t*-stat = –3.499, a decline of 1.39%), *EMR_CDSS* in Column (4) (–0.012, *t*-stat = –3.059, a 1.19% decline), *EMR_CPOE* in Column (5) (–0.017, *t*-stat = –5.386, a 1.69% decline), *EMR_OE* in Column (6) (–0.016, *t*-stat = –3.741, a 1.59% decline), and *EMR_PD* in Column (7) (–0.009, *t*-stat = –2.862, a 0.90% decline). This suggests that hospitals receive lower average Medicare payments after adopting *all* EMR systems, after adopting *at least one* EMR system, and after adopting *any* of the five individual EMR systems, relative to before adopting an EMR system and to hospitals that have adopted no EMR system. Thus, the results suggest that adoption of any EMR system also leads to reduced Medicare payments.

Paralleling our Table 6, we also replicate these analyses using propensity score matching. Table 8 Panel B presents the results, with findings unchanged from those presented in Panel A above. In particular, we continue to find for the propensity score matched sample that full adoption of all EMR systems, partial adoption of EMR systems, and adoption of any individual EMR system is significantly associated with reduced average payments.

Paralleling our Table 7, we also replicate these analyses using the placebo tests. In particular, we randomly assign the hospital EMR adoption for hospital *h*. Table 8 Panel C presents the results. As with the previous placebo estimations, we fail to find significance for any of the EMR adoption variables. This is consistent with the placebo randomization breaking the link between EMR adoption of reduced payments. That is, this analysis supports the negative association between EMR adoption and decreased payments.

As a final analysis, we examine an alternative dependent variable of *ln*(*Average Medicare Payments*), measured as the log of the average of Medicare payments to the provider for the DRG. In contrast to *ln*(*Average Payments*), this alternative measure excludes co-payments, mitigating potential systematic differences that may occur across hospitals: for example, due to self-selection into certain patient demographics, such as those more able to provide co-payments. Untabulated results are similar to the above findings. We continue to observe significant decreases in average Medicare payments for partial EMR adoption, as well as for adoption of each of the five individual EMR systems. The coefficient on full EMR adoption also is negative but insignificant.

The Effect of Electronic Medical Record Adoption on Service Quality

Next, we examine the effect of EMR adoption on healthcare outcomes. Our results are consistent with expectations that EMR adoption leads to reduced hospital charges through cost efficiencies. However, the goal of any healthcare system and provider is to balance the resources needed to provide services, while ensuring optimal healthcare outcomes. We conduct a preliminary investigation as to whether EMR adoption—while seemingly improving utilization based on the above results—either reduces or enhances healthcare outcomes.

As our proxy for service quality, we use the length of stay.[17] Thus, the new dependent variable is *Inpatient Days*, measured as the average number of inpatient days for all classes of adult and pediatric patients reported by hospital *h* for DRG *d* over year *t*. The treatment and control variables are unchanged from equation (1). If EMR adoption reduces DRG average charges through improved efficiency, but in doing so negatively affects service quality, then we expect average inpatient days to increase (reflecting reduced quality of service, evidenced in patients remaining for longer stays on average). If EMR adoption reduces costs but also improves service

[17] We do not have data for other healthcare outcome proxies, such as readmission rates and mortality. As such, we view this as a preliminary analysis to complement our primary findings regarding the effects of EMR adoption on health care utilization costs.

quality (e.g., by allowing better patient evaluations), then we expect inpatient days to also decrease (or, at least, not to change) coincident with EMR adoption.

Table 9 presents the results. The coefficients on *EMR_All* and *EMR_OE* are significantly negative, with the remaining coefficients on the EMR variables negative although insignificant. These findings provide limited support that EMR adoption also leads to improved service quality, evidenced in reduced patient stays, and no evidence of reduced healthcare quality since none of the EMR coefficients is positive, inconsistent with EMR adoption leading to longer patients stays. We caveat that the chosen proxy (length of stay) can alternatively further capture cost efficiencies; in this latter interpretation, the results remain consistent with our primary findings that EMR adoption leads to reduced hospital charges via reduced costs.

[Insert Table 9 near here]

States Adopting Disclosure Requirements

As a third additional analysis, we investigate the adoption of a price transparency regulation (PTR), which presents a potential confound to our findings.[18] The proposed federal Medicare Payment Rate Disclosure Act of 2013 mandated, beginning in 2013, disclosure by hospitals and providers of their charges for commonly applied DRGs (which generally overlap with the DRGs we examine). Thus, the forced disclosure of these charges in 2013 could drive the observed reduction in hospital utilization costs over the 2011–2015 sample period (versus our examined EMR adoption). This would occur, for example, if the disclosure increases

[18] The Health Information Technology for Economic and Clinical Health (HITECH) Act also was enacted in 2009 by the U.S. Department of Health and Human Services; it provided $27 billion to support and facilitate the adoption of electronic health records in hospitals. As our sample starts in 2011 (and thus our full sample occurs after implementation of the HITECH Act), inferences should be unaffected by its passage.

transparency, enabling hospitals to better compare their charges vis-à-vis competitor and peer hospitals and to adjust them accordingly.

We address this potential confound by examining a subset of states for which mandated disclosure became effective before 2013. In particular, thirty-four states enacted state-level legislation requiring disclosure of DRG charges prior to our sample period (Christensen et al. 2020). Hospitals located within this subset of states thus disclosed these charges throughout our 2011–2015 sample period. Accordingly, we re-estimate our primary analyses on the subset of hospitals located in these states. Untabulated results are generally unchanged from our primary analyses: we continue to find consistently negative associations across virtually all EMR variables for the dependent variables of *ln*(*Average Charges*) and *ln*(*Cost-Charge Ratio*). We note that several are insignificant, likely reflecting diminished power in these specifications (as the number of observations drops by more than 33% across all estimations). Overall, the results of this analysis suggest that our findings do not appear driven by the disclosure requirement of the 2013 act.

VIII. CONCLUSION

This paper examines how the adoption of electronic medical record (EMR) systems affects hospital costs and utilization. EMR systems can enable hospitals to reduce costs by creating efficiencies in the diagnosis, tracking, and providing of healthcare to patients. EMR systems also require considerable ongoing investment, are challenging to implement and integrate, and, if widely adopted, may not lead to comparative benefits vis-à-vis competitor hospitals. We define EMR adoption using five individual EMR systems: the clinical depository system, which maintains up-to-date records of patients; the clinical decision support system, which assists practitioners with diagnosis and treatment plans; the computerized physician order entry system, which allows physicians to enter medical orders; the order entry system, which allows hospitals to replace paper forms with electronic records; and the physician documentation system, which allows physicians to maintain electronic records about patients' conditions.

Our empirical analyses assess whether the collective or individual adoption of these EMR systems leads to lowered health care utilization costs. We use two primary proxies—charges posted by hospitals for individual diagnostic-related groups (DRGs), and hospitals' cost-to-charge ratios, both measured over the period 2011–2015. Results confirm expectations that EMR adoption is associated with lower charges and lower cost-to-charge ratios for the full EMR adoption (i.e., when the hospital has adopted all five examined EMR systems), partial EMR adoption (i.e., when the hospital has adopted any of the five examined EMR systems), and for the adoption of any of the five individual EMR systems. All analyses include fixed effects for hospital and year, as well as for DRG when the dependent variable is charges; this leads to effective within-hospital estimation. We further confirm that our results are robust to implementing a propensity score matching test, a placebo test randomly assigning hospitals to EMR adoption dates, and to accounting for potential serial correlation in the dependent variables. Finally, we provide additional evidence that EMR adoption also is associated with reduced average payments, and limited support that cost efficiencies from EMR adoption do not result in a concurrent reduction in service quality, as the average length of stays also decreases.

Overall, our results provide consistent evidence that EMR adoption appears to be a cost-effective way to reduce healthcare expenditures within hospitals, despite potential offsetting increased costs associated with implementation, integration, and upkeep of these systems. While the economic significance of the effects we document is small, we note that our results constitute a lower bound for the effectiveness of EMRs to contain health care utilization costs. This is because our adoption data is relatively coarse, and does not capture the variation in the degree of user acceptance and utilization (Eldenburg et al. 2010) across hospitals and over time. Future research can examine the effect of this variation, as well as explore specific channels by which the improved costs occur, along with the broader effect of EMR adoption on other healthcare outcomes.

REFERENCES

Agha L (2014) The effect of health information technology on the costs and quality of medical care. *J. Health Econ*. 34:19–30.

American Hospital Association (2005) Forward momentum hospital use of information technology, AHA, http://www.ahapolicyforum.org/ahapolicyforum/resources/content/FINALNonEmbITSurvey105.pdf.

Atasoy H, Chen P, Ganju K (2018) The spillover effects of health IT investments on regional healthcare costs. *Manag. Sci.* 64(6):2515–2534.

Atasoy H, Greenwood B, McCullough J (2019) The digitization of patient care: A review of the effects of electronic health records on health care quality and utilization. *Annu. Rev. Pub. Health* 40:487–500.

Atasoy H, Ganju K, Pavlou P (2021) Do electronic health record systems increase Medicare reimbursements? The moderating effect of the Recovery Audit Program. *Manag. Sci*. Forthcoming.

Bai, G., Anderson G F (2015). Extreme Markups. The Fifty US Hospitals with the Highest Charge-to-Cost Ratio. *Health Aff.* 34(6): 922-928.

Bai, G., Anderson G F (2016) US Hospitals Are Still Using Chargemaster Markups To Maximize Revenues. *Health Aff* 35 (9):1658-1664.

Bardhan I, Thouin M (2013) Health information technology and its impact on the quality and cost of healthcare delivery. *Decis. Support Syst.* 55(2):438–449.

Bates D (2005) Physicians and ambulatory electronic health records. *Health Aff.* 24(5):1180−1189.

Bates D, Leape L, Cullen D, Laird N, Petersen L, Teich J, Burdick E, Hickey M, Kleefield S, Shea B, Vander Vliet M, Seger D (1998) Effect of computerized physician order entry and a team intervention on prevention of serious medication errors. *J. Am. Med. Assoc.* 280(15):1311–1316.

Bresnahan T, Brynjolfsson E, Hitt L (2002) Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Q. J. Econ.* 117(1):339–376.

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

Centers for Medicare and Medicaid Services (2009) Acute Inpatient Prospective Payment System, https://www.coursehero.com/file/77021357/acutepaymtsysfctshtpdf/.

Christensen H, Floyd E, Maffett M (2020) The only prescription is transparency: The effect of charge-price–transparency regulation on healthcare prices. *Manag. Sci.* 66(7):2861–2882.

Collum T H, Menachemi N, Sen B (2016) Does electronic health record use improve hospital financial performance? Evidence from panel data. *Health Care Manag. Rev*.41(3):267–274.

Cooper Z, Craig V, Gynor M, Reenen J (2019) The price ain't right? Hospital prices and health spending on the privately insured. *Q. J. Econ.* 134(1):51–107.

Devaraj S, Kohli R (2000) Information technology payoff in the healthcare industry: A longitudinal study. *J. Manag. Inf. Syst.* 16(4):41–67.

Dexter P, Perkins S, Maharry K, Jones K, McDonald C (2004) Inpatient computer-based standing orders vs. physician reminders to increase influenza and pneumococcal vaccination rates: A randomized trial. *J. Am. Med. Assoc.* 292(19):2366–2371.

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

Eldenburg L. (1994). The Use of Information in Total Cost Management. *The Accounting Review*, 69(1): 96–121.

Eldenburg L, Soderstrom N, Willis V, Wu, A (2010). Behavioral changes following the collaborative development of an accounting information system. *Accounting, Organizations and Society*, 35(2): 222–237.

Farley D, Hogan C (1990) Case mix specialization in the market for hospital services. *Health Serv. Res.* 25(5):757–783.

Fichman R, Kohl R, Krishnan R (2011) Editorial Overview—The Role of Information Systems in Healthcare: Current Research and Future Trends. *Information Systems Research* 22(3):419-428.

Ford EW, Menachemi N, Peterson LT, Huerta TR (2009) Resistance is futile: but it is slowing the pace of EHR adoption nonetheless. *J. Am. Med. Inform. Assoc.* 16(3):274–81.

Ganju, K. K., Atasoy, H., McCullough, J., Greenwood, B., (2020) The Role of Decision Support Systems in Attenuating Racial Biases in Healthcare Delivery. *Manag. Sci.*, 66(11):5171-5181.

Goldschmidt, P. (2005) HIT and MIS: Implications of health information technology and medical information systems. Common. ACM 48:68-74.

Hawaii Medical Service Association (2018) Diagnosis-related groups, https://prc.hmsa.com/s/.

Healthcare Financial Management Association (2006) Overcoming barriers to electronic health record adoption: Results of survey and roundtable discussions conducted by the Healthcare Financial Management Association. http://www.providersedge.com/ehdocs/ehr_articles/Overcoming_Barriers_to_EHR_Adoption.pdf

Hersh, W. (2004) Health care information technology: Progress and barriers. *J. Am. Med. Assoc.* 292(18):2273-2274.

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

Huang, S., Avery, T., Song, Y., Elkins, K., Nguyen, C., Nutter, S., Nafday, A., Condon, C., Chang, M., Chrest, D., (2010) Quantifying interhospital patient sharing as a mechanism for infectious disease spread. *Infect. Control Hosp. Epidemiol.* 31(11):1160-1169.

Kellermann, A., Jones, S., (2013) What it will take: The as-yet-unfulfilled promises of health information technology. *Health Aff.* 32(1):63-68.

Kim. (1988). Organizational Coordination and Performance in Hospital Accounting Information Systems: An Empirical Investigation. *The Accounting Review*, 63(3):472–489.

Kim, H., Lee, J., (2020) The impact of health IT on hospital productivity after the enactment of HITECH *Act. Appl. Econ. Lett.* 27(9):719-724.

Krishnan R (2005) The Effect of Changes in Regulation and Competition on Firms' Demand for Accounting Information. *The Accounting Review 80*(1):269–287.

Lee, J., McCullough, J., Town, R., (2013) The impact of health information technology on hospital productivity. *RAND J. Econ.* 44(3):545-568.

Lee, B., McGlone, S., Song, Y., Avery, T., Eubank, S., Chang, C-C., Bailey, R., Wagener, D., Burke, D., Platt, R., (2011) Social network analysis of patient sharing among hospitals in Orange County, California. *Am. J. Pub. Health* 101(4):707-713.

McCullough, J., Michelle-Casey, M., Moscovice, I., Prasad, S., (2010) The effect of health information technology on quality in U.S. hospitals. *Health Aff.* 29(4):647-54.

McCullough, J.S., S. Parente, R. Town. 2016. Health Information Technology and Patient Outcomes: The Role of Organizational and Information Complementarities. *The RAND Journal of Economics* 47(1) 207-236.

Medical Records Institute (2005) Medical Records Institute's sevent annual survey of electronic record trends ad usage for 2005.

Mendez, C., Harrington, D., Christenson, P., Spellberg, B., (2014) Impact of hospital variables on case mix index as a marker of disease severity. *Popul. Health Manag.* 17(1):28-34.

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

Miller, A., Tucker, C., (2011) Can health care information technology save babies? *J. Polit. Econ.* 119(2):289-324.

O'Donnel, B., Schneider, K., Brooks, J., Lessman, G., Wilwert, J., Cook, E., Martens, G., Wright, K., Chrischilles, E., (2013) Standardizing Medicare payment information to support examining geographic variation in costs. *Medicare & Medicaid Res. Rev.* 3(3)

Park, J., Kim, E., Werner, R., (2015) Inpatient hospital charge variability of U.S. hospitals. *J. Gen. Intern. Med.* 30:1627-1632.

Ransbotham, S., Overby, E., Jernigan, M., (2021) Electronic trace data and legal outcomes: The effect of electronic medical records on malpractice claim resolution time. *Manag. Sci. forth*

Reinhardt, U., (2006) The pricing of U.S. hospital services: the chaos behind a heil of secrecy. *Health Aff.* 25(1): 57-69.

Soh, C., Sia, S., (2004) An institutional perspective on sources of ERP package-organisation misalignments. *J. Strateg. Inf. Syst.* 13(4)375-397.

Shen, J., Epane, J., Weech-Maldonado, R., Shan, G., Liu, L., (2015) EHR adoption and cost of care-Evidence from patient safety indicators. *J. Health Care Financ.* 41(4):1-17.

Swartz, N., (2005) Electronic medical records' risks feared. *Inf. Manag. J.* 39(3):9.

Thakkar, M., Davis, D., (2006) Risks, barriers, and benefis of HER systems: A comparative study based on size of hospital. *Perspect. Health Inf. Manag.* 3:5.

Tierney, W., Miller, M., Mcdonalds, C., (1990) The effect on test ordering of informing physicians on the charges for outpatient diagnostic tests. *New England J. Med.* 322(21):1499-1504.

Triplett, J., (1999) The solow paradox: What do computers do to productivity? *Can. J. Econ.* 32(2):309-334.

Wani D, Malhotra M (2018) Does the meaningful use of electronic health records improve patient outcomes? *J. Oper. Manag.* 60:1–18.

Wennberg J, Fisher E, Stukel T, Skinner J, Sharp S, Bronner K (2004) Use of hospitals, physician visits, and hospice care during last six months of life among cohorts loyal to highly respected hospitals in the United States. *BMJ* 328(7440):607.

Appendix A. Electronic Medical Record Systems

System	Abbreviation	Description
Clinical data repository	CDR	Database that is used to maintain an up-to-date record of patients in a single file. These data include information about drug utilization, test results, patient demographics, pathology reports, and discharge summaries.
Clinical decision support system	CDSS	Database that assists medical practitioners with diagnosis and treatment plans.
Computerized physician order entry	CPOE	Database that allows physicians to enter medical orders, which are incorporated with patient information and communicated with laboratories and pharmacies. It includes clinical guidelines for the patients and can flag potential adverse drug reactions.
Order entry	OE	Database that lets hospitals replace paper forms with electronic documents.
Physician documentation	PD	Database that allows physicians to maintain electronic records about patients' conditions and can inform doctors about conditions they may have overlooked.

Notes. This appendix defines each of the five individual electronic medical record systems examined in the paper.

APPENDIX B
Variable Definitions and Sources

Variable	Definition	Source
ln(*Average Charges*)	Log of hospital *h*'s average charge for services covered by Medicare for all discharges for DRG *d* (i.e., sticker price of the procedure) for year *t*.	Medicare Provider Utilization and Payment Data
ln(*Cost-Charge Ratio*)	Log of hospital *h*'s cost-to-charge ratio derived by the reporting hospital based on CMS guidelines (Worksheet S-10, Line 1) for year *t*.	CMS Healthcare Cost Report Information System (HCRIS) Database
ln(*Average Medicare*)	Log of hospital *h*'s average Medicare payments for DRG *d* for year *t*.	Medicare Provider Utilization and Payment Data
ln(*Average Payments*)	Log of hospital *h*'s average Medicare payments for DRG *d* (including the DRG amount, teaching, disproportionate share, capital, and outlier payments for all cases) for year *t*. Also included are co-payment and deductible amounts for which the patient is responsible.	Medicare Provider Utilization and Payment Data
Inpatient Days	Hospital *h*'s reported inpatient days for all classes of adult and pediatric patients for DRG *d* for year *t*.	CMS HCRIS Database
Experimental Variables		
EMR_All	Indicator variable equaling one if hospital *h* has adopted all EMR systems in year *t* and zero otherwise.	HIMSS database
EMR_Partial	Indicator variable equaling one if hospital *h* has adopted at least one EMR system in year *t* and zero otherwise.	"
EMR_CDR *[EMR_CDSS]* *[EMR_CPOE]* *[EMR_OE]* *[EMR_PD]*	Indicator variable equaling one if hospital *h* has adopted the clinical data repository system [clinical decision support system] [computerized practitioner order entry system] [order entry system] [physician documentation system] in year *t* and zero otherwise.	"
Control Variables		
Discharge	Number of discharges billed by hospital *h* for inpatient hospital services for year *t*.	HIMSS database
Beds	Number of licensed beds for hospital *h* for year *t*.	"
IC_Beds	Number of intensive care beds for hospital *h* for year *t*.	"
CMI	Case mixed index for hospital *h* for year *t*, with a higher *CMI* indicating a more complex and resource-intensive case load.	"

EMR_HSA	Average EMR adoption of other hospitals in the same HSA except for the focal hospital for year *t*.	“
Unemployment	Unemployment rate for year *t*.	American Community Survey
Income	Mean household income in 2019 adjusted dollars for year *t*.	“
Education	Percentage of people having a bachelor’s degree or higher for year *t*.	“
Population	Log transfer of total population for year *t*.	“
Sex_Ratio	Number of males per 100 females for year *t*.	“
Age_Ratio	The combined under 18 and over 65 populations divided by the 18-to-64 population, and multiplied by 100 for year *t*.	“

TABLE 1
Sample Selection

Sample Selection Criterion	Number of Hospitals	Years Included	Number of DRGs	Number of Hospital-Years	Number of Hospital-Year-DRGs
Providers in the CMS data set	2,753	2011–2015	565	12,166	644,754
Providers in the HIMSS data set	2,690	2009–2015	N/A	11,769	N/A
Geographic characteristics from the American Community Survey	1,457	2011–2015	N/A	6,004	N/A
Final sample	**1,457**	2011–2015	539	6,004	**147,318**

Notes. This table presents the sample selection. The sample period is 2011–2015. The unit of observation is the hospital-year-DRG. DRG (CMS) [HIMSS] refers to diagnostic-related group (Centers for Medicare and Medicaid Services) [Healthcare Information Management Science Society]. N/A indicates unavailable.

TABLE 2
Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum
Dependent Variables				
Ln(*Average Charges*)	10.548	0.774	7.678	14.843
Ln(*Cost-Charge Ratio*)	0.220	0.102	0	0.696
Average Charges	53,105	59,342	2,159	2,794,184
Cost-Charge Ratio	0.253	0.141	0	1.005
Ln(*Average Payments*)	9.186	0.635	7.844	12.982
Average Payments	12,442	12,341	2,550	434,396
Ln(*Average Medicare*)	8.998	0.691	7.193	12.798
Experimental Variables				
EMR_All	0.616	0.486	0	1
EMR_Partial	0.917	0.275	0	1
EMR_CDR	0.894	0.308	0	1
EMR_CDSS	0.900	0.300	0	1
EMR_CPOE	0.730	0.444	0	1
EMR_OE	0.899	0.301	0	1
EMR_PD	0.670	0.470	0	1
Control Variables				
Discharge	3.360	0.749	2.398	7.659
Beds	419.990	245.551	8	2,101
IC_Beds	33.630	37.537	0	607
CMI	1.667	0.235	0.599	3.847
EMR_HSA	0.676	0.250	0	1
Unemployment	5.165	1.641	1.1	12.8
Income	11.103	0.220	10.599	11.781
Education	31.626	10.159	9.6	70.4
Population	13.139	1.150	11.066	16.135
Sex_Ratio	95.620	4.103	84.8	163.8
Age_Ratio	58.660	9.728	32.9	105.4

Notes. This table presents the descriptive statistics for the variables used in the analyses. For all variables, N = 147,318 diagnostic-related group (DRG)-hospital-year observations.

TABLE 3
Correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Average Charges*	1.000									
(2) *Cost-Charge Ratio*	–0.460	1.000								
(3) *EMR_All*	0.049	–0.029	1.000							
(4) *EMR_Partial*	0.029	–0.171	0.379	1.000						
(5) *EMR_CDR*	0.028	–0.169	0.437	0.867	1.000					
(6) *EMR_CDSS*	0.022	–0.158	0.422	0.898	0.848	1.000				
(7) *EMR_CPOE*	0.021	–0.007	0.771	0.492	0.521	0.516	1.000			
(8) *EMR_OE*	0.037	–0.178	0.424	0.894	0.903	0.882	0.525	1.000		
(9) *EMR_PD*	0.052	–0.067	0.888	0.427	0.448	0.446	0.629	0.456	1.000	
(10) *Discharge*	–0.089	0.014	–0.020	–0.007	–0.000	0.000	–0.019	–0.002	–0.016	1.000
(11) *Beds*	0.147	0.054	0.130	–0.050	–0.034	–0.037	0.122	–0.016	0.108	0.157
(12) *IC_Beds*	0.063	0.072	0.118	0.031	0.017	0.040	0.080	0.014	0.119	0.090
(13) *CMI*	0.234	–0.072	0.105	–0.007	–0.035	–0.031	0.103	–0.017	0.078	0.068
(14) *EMR_HSA*	0.104	–0.135	0.209	0.112	0.122	0.109	0.224	0.120	0.173	–0.043
(15) *Unemployment*	0.011	–0.027	–0.258	–0.021	–0.021	–0.041	–0.232	–0.044	–0.216	0.069
(16) *Income*	0.040	0.210	0.056	–0.008	–0.022	–0.007	0.056	–0.041	0.024	–0.002
(17) *Education*	0.019	0.227	0.098	–0.040	–0.046	–0.038	0.080	–0.071	0.060	0.002
(18) *Population*	0.222	–0.027	0.044	–0.039	–0.024	–0.057	0.049	–0.042	0.025	–0.004
(19) *Sex_Ratio*	0.029	–0.098	–0.019	0.040	0.024	0.030	–0.030	0.016	–0.012	–0.048
(20) *Age_Ratio*	0.010	-0.198	0.029	0.066	0.080	0.081	0.019	0.100	0.069	–0.005

Variable	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(11) *Beds*	1.000									
(12) *IC_Beds*	0.469	1.000								
(13) *CMI*	0.547	0.323	1.000							
(14) *EMR_HSA*	0.038	0.004	0.049	1.000						
(15) *Unemployment*	0.023	–0.015	–0.084	–0.134	1.000					
(16) *Income*	0.069	0.050	0.062	0.047	–0.178	1.000				
(17) *Education*	0.213	0.097	0.234	0.079	–0.209	0.739	1.000			
(18) *Population*	0.241	0.148	0.171	0.118	0.200	0.381	0.278	1.000		
(19) *Sex_Ratio*	–0.219	–0.097	–0.034	–0.112	–0.141	0.059	–0.113	–0.070	1.000	
(20) *Age_Ratio*	–0.213	–0.070	–0.235	0.099	–0.076	–0.321	–0.571	–0.197	–0.073	1.000

Notes. This table presents Spearman correlations for the variables. All correlations are significant at the 10% level or greater. *N* = 147,318 diagnostic-related group (DRG)-hospital-year observations

TABLE 4
The Effect of Electronic Medical Record Adoption on Hospital Utilization Costs

		Dependent Variable			
Variable	**Prediction**	***ln*(*Average Charges*) (*N* = 147,318)**		***ln*(*Cost-Charge Ratio*) (*N* = 5,195)**	
		(1)	(2)	(3)	(4)
EMR_All	**(–)**	**–0.008**		**–0.012 *****	
		(–1.121)		**(–3.270)**	
EMR_Partial	**(–)**		**–0.040 *****		**0.008**
			(–3.884)		**(0.878)**
Discharge	(–)	–0.022 ***	–0.022 ***	–0.000	–0.000
		(–10.803)	(–10.783)	(–0.070)	(–0.112)
Beds	(–)	–0.001 *	–0.001 *	0.000***	0.000***
		(–1.763)	(–1.677)	(2.703)	(2.779)
IC_Beds	(–)	0.000	0.000	–0.000	–0.000
		(1.064)	(1.019)	(–0.886)	(–0.913)
CMI	(+/–)	–0.063	–0.059	0.030	0.029
		(–1.593)	(–1.526)	(1.469)	(1.422)
EMR_HSA	(–)	–0.048 ***	–0.040 ***	0.006	0.003
		(–3.519)	(–2.949)	(0.854)	(0.488)
Unemploy	(–)	–0.002	–0.002	–0.002	–0.001
		(–0.578)	(–0.654)	(–0.964)	(–0.865)
Income	(–)	–0.032	–0.028	–0.254*	–0.256*
		(–0.642)	(–0.559)	(–1.735)	(–1.775)
Education	(+)	0.002	0.001	0.001*	0.001*
		(1.195)	(1.070)	(1.701)	(1.713)
Population	(–)	–0.013	–0.012	–0.037	–0.036
		(–1.191)	(–1.106)	(–1.086)	(–1.095)
Sex_Ratio	(+)	0.000	0.000	–0.001	–0.001
		(0.172)	(0.010)	(–0.608)	(–0.639)
Age_Ratio	(+)	0.003 **	0.003 ***	–0.005***	–0.005***
		(2.511)	(2.638)	(–3.288)	(–3.364)
Fixed effects		DRG, hospital, year	DRG, hospital, year	hospital, year	hospital, year
Adjusted R^2		0.933	0.933	0.984	0.979

Notes. This table presents regression results examining the effect of electronic medical records (EMR) adoption on hospital utilization costs. In Columns (1) and (2), the dependent variable is *ln*(*Average Charges*), the log of hospital *h*'s average charge for diagnosis-related group (DRG) *d* covered by Medicare for year *t*. In Columns (3) and (4), the dependent variable is *ln*(*Cost-Charge Ratio*), hospital *h*'s ratio of total Medicare allowable cost divided by total charges posted for Medicare patients for year *t*.

The experimental variables (bolded) are: *EMR_All*, an indicator variable equaling one if hospital *h* has adopted all five EMR systems in year *t*, and zero otherwise; and *EMR_Partial*, an indicator variable equaling one if hospital *h* adopts at least one EMR system in year *t*, and zero otherwise. See Appendix A for definitions of the five individual EMR systems. All other variables are defined in Appendix B.

Regressions with *ln*(*Average Charges*) as the dependent variable include fixed effects for DRG, hospital, and year; regressions with *ln*(*Cost-Charge Ratio*) as the dependent variable include fixed effects for hospital and year. *t*-statistics are shown in parentheses and reflect robust standard errors clustered at the hospital-year level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively, for the indicated one- or two-tailed tests.

TABLE 5
Individual Electronic Medical Record Systems

	EMR_CDR	***EMR_CDSS***	***EMR_CPOE***	***EMR_OE***	***EMR_PD***
	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable = *ln*(*Average Charges*) (*N* = 147,318)					
***EMR Variable* (–)**	**–0.034 *** (–3.846)**	**–0.033 *** (–3.537)**	**–0.020 *** (–2.837)**	**–0.033 *** (–3.419)**	**–0.016 ** (–2.316)**
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.933	0.933	0.933	0.933	0.933
Panel B: Dependent Variable = *ln*(*Cost-Charge Ratio*) (*N* = 5,195)					
***EMR Variable* (–)**	**0.002 (0.293)**	**0.008 (1.156)**	**–0.014 *** (–3.843)**	**0.004 (0.596)**	**–0.009 ** (–2.169)**
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year
Adjusted R^2	0.979	0.979	0.979	0.979	0.979

Notes. This table presents regression results examining the effect of adoption of individual electronic medical record (EMR) systems on hospital utilization costs. In Panel A, the dependent variable is *ln*(*Average Charges*), the log of hospital *h*'s average charge for diagnosis-related group (DRG) *d* covered by Medicare for year *t*. In Panel B, the dependent variable is *ln*(*Cost-Charge Ratio*), hospital *h*'s ratio of total Medicare allowable cost divided by total charges posted for Medicare patients for year *t*.

The experimental variables (bolded) are as follows. In Column (1), *EMR_CDR* is an indicator variable equaling one if hospital *h* has adopted the clinical data repository (CDR) EMR in year *t*, and zero otherwise. In Column (2), *EMR_CDSS* is an indicator variable equaling one if hospital *h* has adopted the clinical decision support system (CDSS) EMR in year *t*, and zero otherwise. In Column (3), *EMR_CPOE* is an indicator variable equaling one if hospital *h* has adopted the computerized physician order entry (CPOE) EMR in year *t*, and zero otherwise. In Column (4), *EMR_OE* is an indicator variable equaling one if hospital *h* has adopted the order entry (OE) EMR in year *t*, and zero otherwise. In Column (5), *EMR_PD* is an indicator variable equaling one if hospital *h* has adopted the physician documentation (PD) EMR in year *t*, and zero otherwise. See Appendix A for definitions of the five systems.

All regressions include the control variables (untabulated) from Equation (1), which are defined in Appendix B. Regressions with *ln*(*Average Charges*) as the dependent variable include fixed effects for DRG, hospital, and year; regressions with *ln*(*Cost-Charge Ratio*) as the dependent variable include fixed effects for hospital and year. *t*-statistics are shown in parentheses and reflect robust standard errors clustered at the hospital-year level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively, for the indicated one-tailed tests.

TABLE 6
Sensitivity Analyses: Propensity Score Matching

Panel A: Treatment and Control Samples

Variable	Treatment	Unmatched Control	Unmatched *t*-statistic	Matched Control	Matched *t*-statistic
	(1)	(2)	(3)	(4)	(5)
Discharge	3.260	3.258	0.04	3.279	–0.49
Beds	283.910	245.220	2.55 **	298.860	–1.11
IC_Beds	23.841	17.710	3.25 ***	26.532	–1.41
CMI	1.556	1.555	0.05	1.551	0.28
EMR_HSA	0.689	0.610	4.43 ***	0.653	2.51 **
Unemployment	4.854	5.584	–6.66 ***	4.898	–0.50
Income	11.139	11.118	1.24	11.122	1.19
Education	31.396	29.904	2.01 **	30.660	1.15
Population	13.149	13.111	0.39	13.170	–0.26
Sex Ratio	96.666	96.853	–0.58	97.165	–1.43
Age Ratio	59.967	59.058	1.48	59.254	1.36

Panel B: Multivariate Analysis with Dependent Variable = Ln(*Average Charges*) (*N* = 85,507)

	EMR_ All	***EMR_ Partial***	***EMR_ CDR***	***EMR_ CDSS***	***EMR_ CPOE***	***EMR_ OE***	***EMR_ PD***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
***EMR* (–)**	**–0.034 *****	**–0.026 ****	**–0.023 ****	**–0.026 ****	**–0.036 *****	**–0.021 ***	**–0.035 *****
	(–2.501)	**(–2.246)**	**(–2.031)**	**(–2.333)**	**(–2.966)**	**(–1.871)**	**(–2.680)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.932	0.932	0.932	0.932	0.932	0.932	0.932

Panel C: Multivariate Analysis with Dependent Variable = Ln(*Cost-Charge Ratio*) (*N* = 3,161)

	EMR_ All	***EMR_ Partial***	***EMR_ CDR***	***EMR_ CDSS***	***EMR_ CPOE***	***EMR_ OE***	***EMR_ PD***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
***EMR* (–)**	**–0.011****	**0.005**	**–0.004**	**0.000**	**–0.014*****	**–0.001**	**–0.006**
	(–2.279)	**(0.561)**	**(–0.522)**	**(0.045)**	**(–2.674)**	**(–0.090)**	**(–1.232)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year
Adjusted R^2	0.979	0.979	0.979	0.979	0.979	0.979	0.979

Notes. This table presents regression results of additional analyses examining the effect of adoption of electronic medical record (EMR) systems on hospital utilization costs using a propensity score matched sample. Panel A presents the matching and mean values of the covariates across the treatment and control samples. In Panel B, the dependent variable is *ln*(*Average Charges*), the log of hospital *h*'s average charge for diagnosis-related group (DRG) *d* covered by Medicare for year *t*. In Panel C, the dependent variable is *ln*(*Cost-Charge Ratio*), hospital *h*'s ratio of total Medicare allowable cost divided by total charges posted for Medicare patients for year *t*.

In Panels B-C, the experimental variables (bolded) are as follows. In Column (1), *EMR_All* is an indicator variable equaling one if hospital *h* has adopted all five EMR systems in year *t*, and zero otherwise. In Column (2), *EMR_Partial* is an indicator variable equaling one if hospital *h* adopts at least one EMR system in year *t*, and zero otherwise. In Column (3), *EMR_CDR* is an indicator variable equaling one if hospital *h* has adopted the clinical data repository (CDR) EMR in year *t*, and zero otherwise. In Column (4), *EMR_CDSS* is an indicator variable equaling one if hospital *h* has adopted the clinical decision support system (CDSS) EMR in year *t*, and zero otherwise. In Column (5), *EMR_CPOE* is an indicator variable equaling one if hospital *h* has adopted the computerized physician order entry (CPOE) EMR in year *t*, and zero otherwise. In Column (6), *EMR_OE* is an indicator variable equaling one if hospital *h* has adopted the order entry (OE) EMR in year *t*, and zero otherwise. In Column (7), *EMR_PD* is an indicator variable equaling one if hospital *h* has adopted the physician documentation (PD) EMR in year *t*, and zero otherwise. See Appendix A for definitions of the five systems.

All regressions include the control variables (untabulated) from Equation (1), which are defined in Appendix B. Regressions with *ln*(*Average Charges*) as the dependent variable include fixed effects for DRG, hospital, and year; regressions with *ln*(*Cost-Charge Ratio*) as the dependent variable include fixed effects for hospital and year. *t*-statistics are shown in parentheses and reflect robust standard errors clustered at the hospital-year level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

TABLE 7
Sensitivity Analyses: Placebo Tests

Panel A: Average Charges (*N* = 147,318)

Experimental Variable	Dependent Variable: *ln*(*Average Charges*)						
	EMR_ All	***EMR_ Partial***	***EMR_ CDR***	***EMR_ CDSS***	***EMR_ CPOE***	***EMR_ OE***	***EMR_ PD***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EMR	**0.000**	**–0.000**	**–0.000**	**–0.000**	**0.001**	**–0.000**	**0.000**
	(0.065)	**(–0.073)**	**(–0.034)**	**(–0.066)**	**(0.118)**	**(–0.061)**	**(0.041)**
Discharge	–0.022***	–0.022***	–0.022***	–0.022***	–0.022***	–0.022***	–0.022***
	(–10.814)	(–10.814)	(–10.814)	(–10.814)	(–10.814)	(–10.814)	(–10.814)
Beds	–0.000*	–0.000*	–0.000*	–0.000*	–0.000*	–0.000*	–0.000*
	(–1.762)	(–1.767)	(–1.764)	(–1.764)	(–1.762)	(–1.764)	(–1.761)
IC_Beds	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.054)	(1.056)	(1.054)	(1.054)	(1.052)	(1.053)	(1.056)
CMI	–0.058	–0.058	–0.058	–0.058	–0.058	–0.058	–0.056
	(–1.475)	(–1.476)	(–1.476)	(–1.476)	(–1.475)	(–1.476)	(–1.474)
EMR_HSA	–0.054***	–0.054***	–0.054***	–0.054***	–0.054***	–0.054***	–0.054***
	(–3.894)	(–3.895)	(–3.894)	(–3.894)	(–3.893)	(–3.895)	(–3.890)
Unemployment	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002
	(–0.749)	(–0.749)	(–0.748)	(–0.748)	(–0.749)	(–0.748)	(–0.749)
Income	–0.043	–0.043	–0.042	–0.042	–0.043	–0.042	–0.042
	(–0.901)	(–0.900)	(–0.899)	(–0.900)	(–0.903)	(–0.900)	(–0.900)
Education	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
	(1.683)	(1.684)	(1.684)	(1.684)	(1.683)	(1.682)	(1.682)
Population	–0.015	–0.015	–0.015	–0.015	–0.015	–0.015	–0.015
	(–1.405)	(–1.408)	(–1.410)	(–1.410)	(–1.410)	(–1.407)	(–1.405)
Sex_Ratio	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.254)	(0.254)	(0.254)	(0.254)	(0.255)	(0.253)	(0.256)
Age_Ratio	0.003**	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(2.868)	(2.869)	(2.869)	(2.870)	(2.869)	(2.870)	(2.868)
Constant	11.207***	11.205***	11.203***	11.204***	11.205***	11.204***	11.204***
	(20.524)	(20.524)	(20.524)	(20.524)	(20.524)	(20.524)	(20.524)
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.933	0.933	0.933	0.933	0.933	0.933	0.933

Panel B: Cost-Charge Ratio (*N* = 5,195)

	Dependent Variable: *ln*(*Cost Charge Ratio*)						
Experimental Variable:	***EMR_ All***	***EMR_ Partial***	***EMR_ CDR***	***EMR_ CDSS***	***EMR_ CPOE***	***EMR_ OE***	***EMR_ PD***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EMR	**0.000**	**0.000**	**0.000**	**–0.000**	**0.000**	**–0.000**	**–0.000**
	(0.006)	**(0.018)**	**(0.002)**	**(–0.001)**	**(0.013)**	**(–0.005)**	**(–0.006)**
Discharge	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(–0.094)	(–0.093)	(–0.093)	(–0.093)	(–0.093)	(–0.093)	(–0.093)
Beds	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(2.764)	(2.763)	(2.765)	(2.764)	(2.764)	(2.764)	(2.765)
IC_Beds	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(–0.884)	(–0.885)	(–0.884)	(–0.884)	(–0.884)	(–0.884)	(–0.883)
CMI	0.030	0.030	0.030	0.030	0.030	0.030	0.030
	(1.452)	(1.452)	(1.451)	(1.451)	(1.451)	(1.452)	(1.452)
EMR_HSA	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.509)	(0.509)	(0.509)	(0.509)	(0.509)	(0.509)	(0.509)
Unemployment	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001
	(–0.857)	(–0.856)	(–0.856)	(–0.856)	(–0.856)	(–0.857)	(–0.857)
Income	–0.258*	–0.258*	–0.258*	–0.258*	–0.258*	–0.258*	–0.258*
	(–1.781)	(–1.781)	(–1.781)	(–1.781)	(–1.780)	(–1.780)	(–1.782)
Education	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(1.746)	(1.745)	(1.746)	(1.746)	(1.746)	(1.746)	(1.745)
Population	–0.037	–0.037	–0.037	–0.037	–0.037	–0.037	–0.037
	(–1.100)	(–1.099)	(–1.100)	(–1.100)	(–1.100)	(–1.100)	(–1.110)
Sex_Ratio	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001
	(–0.652)	(–0.651)	(–0.651)	(–0.652)	(–0.652)	(–0.652)	(–0.651)
Age_Ratio	–0.005***	–0.005***	–0.005***	–0.005***	–0.005***	–0.005***	–0.005***
	(–3.337)	(–3.337)	(–3.337)	(–3.337)	(–3.337)	(–3.337)	(–3.337)
Constant	2.145	2.166	2.192	2.162	2.188	2.188	2.234
	(1.101)	(1.127)	(1.136)	(1.127)	(1.134)	(1.134)	(1.142)
Fixed effects	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year	hospital, year
Adjusted R^2	0.984	0.979	0.979	0.979	0.979	0.979	0.979

Notes. This table presents regression results of additional analyses examining the effect of adoption of electronic medical record (EMR) systems on hospital utilization costs using a placebo test, wherein hospital *h* is assigned to a random EMR adoption time *t*. Assuming our primary analyses address the effect of adoption on hospital charges, we expect this placebo test (i.e., the random assignment of EMR adoption) to show no effect. That is, the randomization will lead to a lack of support for the previously documented negative association between EMR adoption and hospital charges and cost-charge ratio. In Panel A, the dependent variable *ln*(*Average Charges*) is the log of hospital *h*'s average charge for diagnosis-related group (DRG) *d* covered by Medicare for year *t*. In Panel B, the dependent variable is *ln*(*Cost-Charge Ratio*), hospital *h*'s ratio of total Medicare allowable cost divided by total charges posted for Medicare patients for year *t*.

The experimental variables (bolded) are as follows. In Column (1), *EMR_All* is an indicator variable equaling one if hospital *h* has adopted all five EMR systems in year *t*, and zero otherwise. In Column (2), *EMR_Partial* is an indicator variable equaling one if hospital *h* adopts at least one EMR system in year *t*, and zero otherwise. In Column (3), *EMR_CDR* is an indicator variable equaling one if hospital *h* has adopted the clinical data repository (CDR) EMR in year *t*, and zero otherwise. In Column (4), *EMR_CDSS* is an indicator variable equaling one if hospital *h* has adopted the clinical decision support system (CDSS) EMR in year *t*, and zero otherwise. In Column (5), *EMR_CPOE* is an indicator variable equaling one if hospital *h* has adopted the computerized physician order entry (CPOE) EMR in year *t*, and zero otherwise. In Column (6), *EMR_OE* is an indicator variable equaling one if hospital *h* has adopted the order entry (OE) EMR in year *t*, and zero otherwise. In Column (7), *EMR_PD* is an indicator variable equaling one if hospital *h* has adopted the physician documentation (PD) EMR in year *t*, and zero otherwise. See Appendix A for definitions of the five systems.

All control variables are defined in Appendix B. Regressions with *ln*(*Average Charges*) as the dependent variable include fixed effects for DRG, hospital, and year; regressions with *ln*(*Cost-Charge Ratio*) as the dependent variable include fixed effects for hospital and year. *t*-statistics are shown in parentheses and reflect robust standard errors clustered at the hospital-year level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

TABLE 8
Additional Analyses: The Effect of Electronic Medical Record Adoption on Hospital Payments

	Dependent Variable for All Analyses: *ln*(*Average Payments*)						
	EMR_ All	***EMR_ Partial***	***EMR_ CDR***	***EMR_ CDSS***	***EMR_ CPOE***	***EMR_ OE***	***EMR_ PD***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Primary Analyses and Individual EMR Systems (*N* = 147,318)							
EMR **(–)**	**–0.010** *** **(–3.259)**	**–0.013** *** **(–2.752)**	**–0.014** *** **(–3.499)**	**–0.012** *** **(–3.059)**	**–0.017** *** **(–5.386)**	**–0.016** *** **(–3.741)**	**–0.009** *** **(–2.862)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.974	0.974	0.975	0.975	0.975	0.975	0.975
Panel B: Propensity Score Matching (*N* = 85,507)							
EMR **(–)**	**–0.022** *** **(–3.592)**	**–0.020** *** **(–3.892)**	**–0.021** *** **(–4.146)**	**–0.022** *** **(–4.324)**	**–0.021** *** **(–3.958)**	**–0.022** *** **(–4.339)**	**–0.023** *** **(–3.835)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.974	0.974	0.974	0.974	0.974	0.974	0.974
Panel C: Placebo Tests (*N* = 147,318)							
EMR **(–)**	**–0.000** **(–0.020)**	**–0.000** **(–0.041)**	**–0.000** **(–0.027)**	**–0.000** **(–0.074)**	**–0.000** **(–0.014)**	**–0.000** **(–0.010)**	**0.000** **(0.013)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.933	0.933	0.933	0.933	0.933	0.933	0.933

Notes. This table presents additional analyses examining the impact of electronic medical record (EMR) adoption on average hospital payments. Across all panels, the dependent variable is *ln*(*Average Payments*), the log of hospital *h*'s average Medicare payment for DRG *d* covered by Medicare for year *t*. This Medicare payment includes amount, teaching, disproportionate share, capital, outlier payments, co-payment, and deductible amounts. Panel A presents results replicating the primary analyses (i.e., Table 4) and individual EMR systems (i.e., Table 5). Panel B presents results replicating the sensitivity analysis of propensity score matching (i.e., Table 6). Panel C presents results replicating the sensitivity analysis of the placebo test (i.e.,

Table 7).

The experimental variables (bolded) are as follows. In Column (1), *EMR_All* is an indicator variable equaling one if hospital *h* has adopted all five EMR systems in year *t*, and zero otherwise. In Column (2), *EMR_Partial* is an indicator variable equaling one if hospital *h* adopts at least one EMR system in year *t*, and zero otherwise. In Column (3), *EMR_CDR* is an indicator variable equaling one if hospital *h* has adopted the clinical data repository (CDR) EMR in year *t*, and zero otherwise. In Column (4), *EMR_CDSS* is an indicator variable equaling one if hospital *h* has adopted the clinical decision support system (CDSS) EMR in year *t*, and zero otherwise. In Column (5), *EMR_CPOE* is an indicator variable equaling one if hospital *h* has adopted the computerized physician order entry (CPOE) EMR in year *t*, and zero otherwise. In Column (6), *EMR_OE* is an indicator variable equaling one if hospital *h* has adopted the order entry (OE) EMR in year *t*, and zero otherwise. In Column (7), *EMR_PD* is an indicator variable equaling one if hospital *h* has adopted the physician documentation (PD) EMR in year *t*, and zero otherwise. See Appendix A for definitions of the five systems.

All regressions include the control variables (untabulated) from Equation (1), which are defined in Appendix B. All regressions also include fixed effects for DRG, hospital, and year. *t*-statistics are shown in parentheses and reflect robust standard errors clustered at the hospital-year level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

TABLE 9
Additional Analyses: The Effect of Electronic Medical Record Adoption on Service Quality

	Dependent Variable: *Inpatient Days*						
Experimental Variable:	***EMR_ All***	***EMR_ Partial***	***EMR_ CDR***	***EMR_ CDSS***	***EMR_ CPOE***	***EMR_ OE***	***EMR_ PD***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
***EMR* (–)**	**–0.021** * **(–1.897)**	**–0.001 (–0.056)**	**–0.012 (–1.284)**	**–0.012 (–1.219)**	**–0.011 (–1.246)**	**–0.017** * **(–1.740)**	**–0.009 (–1.097)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year	DRG, hospital, year
Adjusted R^2	0.965	0.965	0.965	0.965	0.965	0.965	0.965

Notes. This table presents additional analyses examining the impact of electronic medical record (EMR) adoption on service quality. As our proxy for service quality, the dependent variable is *Inpatient Days*, the average number of days spent by a patient at hospital *h* for diagnosis-related group (DRG) *d* covered by Medicare in year *t*.

The experimental variables (bolded) are as follows. In Column (1), *EMR_All* is an indicator variable equaling one if hospital *h* has adopted all five EMR systems in year *t*, and zero otherwise. In Column (2), *EMR_Partial* is an indicator variable equaling one if hospital *h* adopts at least one EMR system in year *t*, and zero otherwise. In Column (3), *EMR_CDR* is an indicator variable equaling one if hospital *h* has adopted the clinical data repository (CDR) EMR in year *t*, and zero otherwise. In Column (4), *EMR_CDSS* is an indicator variable equaling one if hospital *h* has adopted the clinical decision support system (CDSS) EMR in year *t*, and zero otherwise. In Column (5), *EMR_CPOE* is an indicator variable equaling one if hospital *h* has adopted the computerized physician order entry (CPOE) EMR in year *t*, and zero otherwise. In Column (6), *EMR_OE* is an indicator variable equaling one if hospital *h* has adopted the order entry (OE) EMR in year *t*, and zero otherwise. In Column (7), *EMR_PD* is an indicator variable equaling one if hospital *h* has adopted the physician documentation (PD) EMR in year *t*, and zero otherwise. See Appendix A for definitions of the five systems.

All regressions include the control variables (untabulated) from Equation (1), which are defined in Appendix B. All regressions also include fixed effects for DRG, hospital, and year. *t*-statistics are shown in parentheses and reflect robust standard errors clustered at the hospital-year level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.