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Long-term Effects of Electronic Medical Records on Hospital Clinical, Financial, and Operational Performance

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ABSTRACT

Electronic medical records (EMR) have great potentials to improve healthcare performance. However, there is limited research on the post-adoption effect of EMR on hospital performance. Instead, studies examining the cross-sectional association between EMR and hospital performance have produced mixed findings. This study examines the effects of EMR adoption history defined as the number of years EMR has been implemented in a hospital on clinical, financial, and operational outcomes of U.S. hospitals. We conduct an analysis using multi-year data from 1,417 short-term, general acute care hospitals during 2006 to 2008. The results indicate that EMR adoption history is associated with improved clinical and operational outcomes. With respect to financial outcomes, while EMR adoption history is associated with lower operating cost per patient day, it does not help reduce operating cost per patient admission. The main implication of our research is that (1) hospitals tend to benefit to a greater extent from EMR implementation as they gain more experience with EMR, and (2) the impact of EMR adopt history on hospital costs is not as evident as on clinical and operational performance.

Keywords: Electronic Medical Records, Hospital Performance, Organizational Inertia, Empirical Research

INTRODUCTION

Electronic medical records (EMR) are one of the foundational technologies for the digitization of healthcare. An EMR system is a digital repository of patient data that is fully interoperable and shareable across stakeholders, such as clinicians, insurance companies, employers, and within a hospital (Angst et al., 2010). Typical EMR systems incorporate features such as a clinical data repository (CDR), computerized patient records (CPR), and clinical decision support systems (CDSS) (Angst et al., 2010). EMR can stimulate major shift in the work practices of clinicians and is believed to have a wide range of operational and strategic impact on the business (Makoul, Curry, & Tang, 2001).

EMR offers the promise of unifying fragmented data and applications and allows the practice and administration of medicine to incorporate more evidence-based decision making (Elson & Connelly, 1995). Consequently, the use of EMR should enhance the accuracy of clinical practices such as drug prescription and medication. In addition, the use of EMR can enhance patient care by standardizing routines, further improving quality of healthcare (Queenan, Angst, & Devaraj, 2011). In fact, both government agencies and healthcare providers recognize the potential of EMR to improve quality and efficiency of healthcare. A recent article in Bloomberg Businessweek suggests that EMR is a viable means to tackle the fast growing healthcare costs (Arnst, 2008).

Although EMR has been characterized as one of the significant innovations in the healthcare industry in recent years (Jha, et al., 2009), some researchers argue that the benefits of EMR have yet to be proven and there are unintended consequences with EMR use (Ash, Berg, and Coiera, 2003; Wachter, 2006). While it is widely believed that EMR helps reduce medical errors and improve health, there is no consensus on the extent to which EMR can enhance a hospital's operational and financial performance (Hillestad, et al., 2005; Sidorov, 2006).

A number of studies have investigated the adoption decision and/or the performance impact of various components of EMR in healthcare industry (Angst, et al., 2010; Queenan, et al., 2011). However, the vast majority of these studies utilize a cross-sectional research design. Housman, Hitt, Elo, and Beard (2006) note “previous studies have either utilized cross-sectional analyses or small samples of convenience”. To the best of our knowledge, little research has examined the long-term relationship between EMR adoption history and hospital performance. Literature suggests that the benefits of technology adoption may not be immediate and it takes time for adopting organizations to materialize the benefits of new technologies. A cross-sectional research design makes it difficult for researchers to control for the omitted hospital-level factors that may confound the EMR-adoption and performance relationship. In contrast, longitudinal data can often improve the accuracy of the results by detecting lag effects and by controlling for firm-specific effects (Kohli and Devaraj, 2003).

Although a substantial body of literature has examined the relationship between information technology adoption and hospital performance, only a handful of such studies have focused on the performance impact of EMR. Related studies on this topic tend to examine a limited set of performance measures. However, it is unclear whether EMR enables hospitals to improve performance along multiple dimensions. The piecemeal approach to examining the EMR performance impact does not adequately answer this question. For instance, hospitals often need to make substantial investments to improve clinical performance, likely leading to deteriorated financial performance for an extended period of time. Thus, focusing on financial performance or clinical performance alone can lead to incorrect conclusion about the real benefits of EMR. It is likely that EMR may lead to improved performance in some areas while compromising performance in other areas. Without examining a broad set of performance matrices, it is difficult to assess the overall impact of EMR on hospital performance.

To tackle the above limitations of the existing literature, our study examines the longitudinal impact of EMR adoption on a variety of hospital clinical, financial, and operational performance measures. We capture not only whether a hospital has EMR in place for a given year, but also the history of EMR adoption, as measured by the number of years since the EMR was completely adopted by a hospital. We label this variable "EMR adoption history". We compiled a multi-year dataset using three archival data sources, including EMR adoption data from Health Information Management Systems Society (HIMSS) annual survey, hospital performance data from Hospital Quality Alliance (AHQ), and financial and operational data from American Hospital Directory. The dataset enables us to observe the lag effect of EMR adoption while controlling the fixed effect of each hospital, thus moving a step closer toward understanding the causal relationship between EMR adoption and hospital performance (Kohli and Devaraj, 2003; Tsikriktsis, 2007). We found that EMR adoption history was associated with improved clinical and operational outcomes. While EMR adoption was associated with lower operating cost per patient day, it did not help reduce operating cost per patient admission. Our findings provide rigorous and detailed empirical evidence on the benefits of EMR adoption. These findings can potentially be use to make the business case to adopt EMR.

In what follows, we first review extant research on EMR. We then develop hypotheses linking EMR to hospital performance. The hypotheses are tested with several multi-year national databases. We conclude with a discussion of the findings' implications for theory and practice.

LITERATURE AND HYPOTHESES

Background of EMR

EMR refers to electronic records of health-related information on patients that can be created, gathered, managed, and consulted by authorized clinicians and staff within a healthcare organization (National Alliance for Health Information Technology, 2008). EMR has a great potential to improve healthcare performance. First, EMR can improve operational efficiency by reducing the retrieval time for patient charts and by making those charts available to multiple stakeholders, including physicians, staff, and patients. Second, EMR can reduce medical errors. For instance, basic use of EMR such as computerized physician order entry (CPOE) can greatly improve the legibility and accessibility of progress notes and reduce adverse drug events by warning about potentially harmful interactions of a new drug with other drugs (Goodman, 2005).

Despite the potential benefits of EMR, the EMR adoption rate in hospitals within the United States has lagged behind that of similar enterprise information technology in other industries by more than 20 years (Jha, et al., 2009). According to the EMR adoption model (EMRAM) by HIMSS Analytics, there are seven stages of EMR capabilities (See Table 1). The vast majority of the US hospitals are still in the initial stage of EMR implementation, with only 13.6% hospitals equipped with closed loop medication administration or higher capabilities by the 3rd quarter of 2011 (i.e., stages 5-7). As delineated by the EMRAM, hospitals may encounter greater barriers including interoperability requirements, technology integration, and process redesign as they move to higher stages. Yet the return on investment (ROI) and other benefits will not be realized until hospitals have fully implemented a closed loop medication administration environment (i.e., stages 5-7), in which auto-identification technologies are integrated with CPOE and pharmacy to maximize point-of-care patient safety processes for medication administration.

< Insert Table 1 about Here>

Past research on EMR and hospital performance

Past research on EMR tends to focus on limited performance measures. For instance, Queenan et al. (2011) examine the effect of CPOE adoption and extent of use on customer satisfaction. Angst et al. (2010) relate sequence of medical technology adoption to cost and quality performance of hospitals. Furukawa and his colleagues use multiple databases from national and state health agencies to study the effects of EMR implementation on staffing efficiency (Furukawa, Raghu, and Shao, 2010a, 2010b; Furukawa, Raghu, and Shao, 2011). Past empirical research has seldom examined the long-term impact of EMR on hospital performance. Instead, several studies use simulation methods to analyze the longitudinal impact of EMR. For instance, Walker, et al. (2005) build a cost-benefit model based on expert inputs to estimate the long-term implementation costs and cost savings of a broadly adopted and interoperable EMR system in the United States. Using cost data from the literature and provider inputs, Hillestad et al. (2005) use simulation models to estimate the cumulative potential net efficiency and safety savings from the practice of EMR systems over a period of fifteen years.

Studies examining the association between EMR and hospital performance have produced mixed findings (See Table 2). A stream of research suggests that healthcare IT systems such as EMR can 1) reduce recordkeeping time (i.e., prescription, test orderings, and care management reminders), 2) improve staff productivity, and 3) reduce mortality risk (Barlow, Johnson, and Steck, 2004; Furukawa et al., 2010; Gonzalez-Heydrich et al., 2000; Sachs, 2003; Thompson, Classen, and Haug, 2007). However, other research suggests that an EMR system can reduce production efficiency and increase medical errors when it is not aligned with current existing workflow (Parente and Van Horn, 2006; Sidorov, 2006; Wachter, 2006; Walker, et al., 2005). In addition, researchers argue that productivity and profit payoffs of healthcare IT follow a learning curve effect. In other words, costs decrease as the adopting organizations gain experience with the technology (Chaiken, Christian, and Johnson, 2007; Devaraj and Kohli, 2000; Housman, et al., 2006).

< Insert Table 2 about Here>

Hypotheses

The main theses of our propositions are two folds. First, the impact of EMR adoption is not immediate, but rather increases as hospitals accumulate experience with EMR. Thus, EMR adoption history should be positively related to hospital performance. Second, EMR will impact different types of hospital performance to different extents because of the structural inertia of hospitals and EMR users' attitude and behavior intention. We synthesize multiple literature streams to develop our research hypotheses, including organizational inertia, IT business value, and individuals' technology acceptance and usage behavior.

EMR is a highly complex technology innovation. Since EMR changes how physicians and nurses pull, file, and maintain medical records, it represents one of the major challenges to the existing organizational routines embedded in hospital operations. Successful EMR adoption requires organizational-level efforts to redesign business processes associated with EMR and user-level efforts to overcome the knowledge burden (Jha, et al., 2009). IT business value literature suggests that successful ERP implementation requires business process redesign, which can drastically change the status quo of the existing processes (Melville et al., 2004).In the short run, steep learning curves can degrade already efficient and focused workflow. Indeed, empirical research on ERP reports that operational performance does not necessarily improve immediately following the implementation of ERP systems (McAfee, 2002). The adopting firms usually move down the learning curve over time and gradually realize the benefit of ERP. Several studies highlight the longer-term impact of innovative managerial practices on the process level performance of hospitals (Goldstein and Iossifova, 2011) and other service settings (Heim and Ketzenberg, 2011).

The benefits of complex technology innovation cannot be realized by a few users independently. Rather, "technology use and other outcomes depend on implementation activities that must be coordinated and synchronized across many adopters who may be distributed across multiple departments or geographic locations" (Gallivan, 2001, p.56). In the case of EMR implementation, its full benefits cannot be materialized until multiple stakeholders including physicians, nurses, IT support staff, vendors, and possibly patients synchronize the use of EMRs in daily routine practices. Benefits from EMR adoption can only accrue when they are done in concert with other organizational initiatives over an extended period of time (Devaraj & Kohli, 2000).

At the user level, a complex system such as EMR will likely create knowledge burdens on individual users. EMR systems are challenging to use partly because of the multiplicity of screens, options, and navigational aids. Literature suggests that when users lack incentives to use a new technology, they will likely avoid using the technology or find ways to work around the technology (Boudreau and Robey, 2005). In the case of EMR, users' attitudes and beliefs toward EMR can change quite slowly during the course of their EMR use. However, the greatest benefits can only accrue when physicians overcome the technology barriers and use EMR capabilities for most of their daily tasks, which might take years to realize.

Compared with ERP implementation in manufacturing industries, the unique characteristics of the hospital industry can lead to even longer time for the potential EMR benefits to realize. First, Hospitals tend to subject to strong structural inertia (Hannan and Freeman, 1984). Hospitals are not subject to strong market forces partly due to government regulations and the large proportion of nonprofit ownership. Strong institutional forces can significantly slow the rate of change in hospital industry. "The presence of professional and accrediting bodies resists the incursion of market forces and any changes that threaten professional prerogatives. And the regionally based character of healthcare delivery resists uniform technological solutions and standards" (Burns, 2002, p. 16). As a case in point, statewide privacy regulations restricting hospital release of health information can reduce aggregate EMR adoption by more than 24% (Miller and Tucker, 2009).

Second, despite the consolidation effort in recent decades, healthcare industry is still fragmented, complicating the task of connecting various parties and standardizing the formats and content of business transactions. As a result, existing electronic data resources (e.g., laboratory systems, pharmacy systems, and physician dictation systems) still largely reside on isolated islands with different structures, different levels of granularity, and different coding systems (Hillestad, et al., 2005; McDonald, 1997), creating significant barriers to realizing EMR benefits. Past research suggests that one of the major barriers to EMR use is the lack of electronic data exchange between EMR and other clinical data systems (e.g., laboratory, radiology, and pharmacy systems). For EMR implementation not fully integrated into the hospital information systems, physicians may have to switch between systems to manually enter and verify data from external systems, slowing down workflow and increasing physicians' resistance to EMR use (Miller and Sim, 2004).

Third, decentralized decision making to the frontline professional workers (e.g., physicians, nurses) in many hospitals makes it difficult to mandate the use of EMR to physicians. Although physicians are often reluctant to fully adopt EMR for reasons such as limited computer literacy and concerns over productivity loss, it is difficult for the hospital management to mandate the use of EMR as a way to push the adoption of EMR.

Based on the above discussion, the complexity of EMR, along with the unique nature of hospital industry can make EMR implementation a prolonged process. We expect that hospitals that have used EMR longer should reap greater benefits from using EMR.

H1: EMR adoption history should be positively associated with hospital performance.

Organizations in general value reliability and accountability. In many industries, external stakeholders may emphasize reliability over efficiency (Kelly and Amburgey, 1991). Pressures for reliability and accountability are intense when substantial risks exist, as is the case with hospitals, which are expected to use qualified healthcare professionals and strictly follow protocols and norms in treating patients (Hannan and Freeman, 1984). High quality and reliable healthcare as reflected by superior clinical quality performance are deemed most important and visible performance measures of a hospital. Until recently, hospitals are evaluated and rewarded mainly by quality of healthcare, and to a lesser extent by efficiency (Pear, 2011). For instance, various rankings of hospitals (e.g. US News and World report best hospitals) tend to focus on clinical related matrices including *patient survival*, *patient safety*, and *care-related factors* such as nursing and patient services (Comarow, 2011). Given the historical emphasis on healthcare quality and the potential quality and efficiency tradeoff observed in healthcare providers, hospital management may have higher expectation for EMR to improve quality than efficiency. The high initial costs of EMR implementation can also lower management's expectation regarding the financial returns of EMR.

At the user level, physicians and nurses are not likely to be held accountable for using expensive procedures or materials for quality reasons. Also, the presence of third-party payment (e.g., Medicare, Medicaid insurances) buffers physicians from the immediate financial consequences of their decisions. Physicians may avoid using EMR to improve efficiency if doing so requires significant additional efforts. This view is consistent with the prescription of the diffusion of innovation theory (Rogers, 1983) and the technology acceptance model (Davis, 1989), which suggest that *performance expectancy* and *effort expectancy* are among the main factors that affect the individual's extent of use of a new technology.

The benefits of EMR in preventing mistakes and reducing errors are likely viewed as more important by physicians than the potential opportunities for improving efficiency by using EMR. While many EMR benefits may be visible at the system level, users may perceive EMR as a burden because of the high initial physician time costs. EMR implementation usually incurs high up-front financial costs, estimated at $16,000 to $36,000 per physician (Miller and Sim, 2004). Due to the difficulties with technology and complementary changes, most physicians using EMR spend more time per patient for months and even years after EMR adoption (Miller and Sim, 2004). Physicians may either avoid using some functions of EMR or find ways to work around the system constraints in unintended ways which physicians consider to work best from their own perspective. We use computerized physician order entry (CPOE), an EMR component, as an example. Many physicians appreciate the value of CPOE in preventing medical errors. However, CPOE also creates burdens to physicians since they have to switch from handwriting physician orders to entering the order into a computer system. Thus, it is not uncommon that physicians who have already adopted CPOE still write their orders manually and a pharmacist or clerk will then enter the orders into the computerized system to conform to the CPOE requirements. The piecemeal or partial use of EMR may reduce its overall performance impact, leading to weak performance effects in some areas.

To summarize the above argument, the institutional forces that drive hospitals to focus on healthcare quality may drive the use of EMR to improve healthcare quality and clinical performance over efficiency, resulting in less significant financial impact. Thus, we propose the following:

> *H2: EMR adoption history should have a stronger association with clinical performance than with operational performance and financial performance.*

METHODOLOGY

Sample Description

The sample for this study is a comprehensive multi-year data set that we built by combining three national databases with respect to hospitals' technology application, performance, characteristics, and demographics. We first derived the technology application data from an annual survey of hospitals in the United States, conducted by the Health Information Management Systems Society (HIMSS). The data contain facility-specific technology application status for each hospital from 1985 to 2008. The second data source is the hospital performance database provided by Hospital Quality Alliance (AHQ), a consortium of public and private groups, which tracks the performance and patient volumes of hospitals nationwide. The data contain process quality indictors including heart attack, heart failure, and pneumonia from 2006 to 2008. The third data source is the hospital directory from American Hospital Association, which provides both financial and operational data as well as hospital characteristics such as hospital size, urban/rural designation, and ownership type.

We derived our final sample by matching hospitals that reported their IT application status in HIMSS database (we eliminated the hospitals that did not report EMR status) to those hospitals listed in all other two databases. By merging the three databases, we obtained 3,622 observations for 1,417 short-term acute care hospitals from 2006 to 2008.

Description of Study Variables

<u>Input variables: EMR status & EMR adoption history</u>

Drawing on the literature, we treat EMR adoption as a dichotomous variable that is derived from three major indicators: clinical data repository (CDR), clinical decision support system (CDSS), and computerized patient records (CPR) (Angst, et al., 2010; Bower, 2005). For a hospital in a particular year, we coded EMR status (*ERST*) as a “1” if a hospital has adopted all three components by that year (i.e., CDR, CDSS, and CPR). *ERST* was coded as a “0” if any of the three components has not been adopted by the hospital by that year. We assume that once the EMR is adopted, it remains in place throughout our study period (2006-2008). By examining HIMSS databases from 1985 to2008, we were able to track down the adoption history for each single hospital in the database. We subtracted the adoption year from the current observation year and derived the EMR adoption history for all hospitals (e.g., $ERAH = Year_{current} - Year_{Adopted}$).

Output variables: Operational outcome

We measured operational performance of our sample hospitals with two indicators: occupancy and efficiency. We defined occupancy for a hospital as the actual usage of licensed beds by pooling all adjusted patient days of the hospital (e.g., $OCPY = \frac{no\ of\ adjusted\ patient\ days}{365 \times licensed\ beds}$). We defined efficiency as the productivity of each full time equivalent employee (FTE) by pooling all adjusted patient days (e.g., $EFCY = \frac{no\ of\ adjusted\ patient\ days}{365 \times FTE}$). Both measures indicate the utilization rates for the hospital facility (i.e., beds and employees).

Output variables: Clinical outcome

We used quality and volume data collected by AHQ to assess the clinical performance for three different processes: acute heart attack, congestive heart failure, and pneumonia. The published measures of these three different processes have been widely endorsed and considered valid and feasible for immediate public reporting (Jha, Li, Orav, and Epstein, 2005). The quality measures are as follows:

The variable *Heart attack* (*HTAT*) is derived from eight measures: (1) aspirin at arrival, (2) aspirin at discharge, (3) beta-blocker at arrival, (4) beta-blocker at discharge, (5) ACE inhibitor or ARB for left ventricular systolic dysfunction, (6) smoking cessation counseling, (7) fibrinolytic medication within 30 minutes of arrival, and (8) PCI within 90 minutes of arrival.

The variable *Heart failure* (*HTFR*) utilizes the following four variables: (1) left ventricular function assessment, (2) ACE inhibitor for left ventricular systolic dysfunction, (3) smoking cessation counseling, and (4) discharge instructions.

The variables *Pneumonia* (*PUMA*) is built on seven variables: (1) influenza vaccination, (2) pneumococcal vaccination, (3) initial antibiotic(s) within 4 hrs' arrival, (4) oxygenation assessment, (5) smoking cessation counseling, (6) most appropriate initial antibiotic(s), and (7) initial emergency room blood culture prior to first dose of antibiotic(s).

We used the approach by Theokary and Ren (2011) and measured the weighted average quality score for condition *c* and hospital *h* as

$$q_{ch} = \frac{\sum_{m=1}^{m_c} N_{cmh} \times s_{cmh}}{N_{ch}}$$

where q_{ch} captures the percentage of patients suffering from condition *c* who received the best practice treatment from hospital *h*. N_{cmh} denotes the number of patient cases hospital *h* handles for measure *m* and condition *c*, and s_{cmh} denotes the associated quality score for measure *m*.

Output variables: Financial outcome

Following the health care efficiency typology (Hussey, et al., 2009), we measured financial outcome with two indicators. Operating cost per patient day (*CSTD*), calculated using the ratio of $\frac{\text{Total operating expense}}{\text{Adjusted patient days}}$, which measures the cost to the hospital per adjusted patient day. The second variable of operating cost per patient admission (*CSTA*), calculated as the ratio of $\frac{\text{Total operating expense}}{\text{Adjusted patient admissions}}$, which captures the cost to the hospital per patient stay. By including two indictors of operational efficiency – cost per day and cost per admission, we can avoid the bias resulting from patients' varying length of stay (Devaraj & Kohli, 2000). We derived both measures from AHA database and adjusted them with the Producer Price Index for hospitals to remove macroeconomic and time effects across observations.

Control variables: Hospital characteristics

We include in our model relevant factors that may also affect performance. For our research study, it is critical to identify factors that might cause large differences in performance across hospitals as well as factors that may vary systematically across years within each hospital. Therefore, we conducted an extensive literature survey of studies on determinants of healthcare performance. The list and labeling of control variables that we employ in our study reflect the extant literature in healthcare management (Becker and Sloan, 1985; Devaraj and Kohli, 2000; Hussey et al., 2009; Ozcan, Luke, and Haksever, 1992).

District (*DIST*): The sample hospitals can be segmented into four groups based on their service regions (e.g., Northeastern, Midwest, South, and West). We control for regions to assure that observed performance differences were not merely the consequence of regional variations.

Staffed bed size (*BEDS*): The number of staffed beds provides a measure of the available capacity at a hospital. Research suggests that capacity and performance may be significantly associated and therefore the effect of capacity should be controlled for.

Service index (*CASM*): The index is constructed as the average diagnosis-related group weight for all of a hospital's patient volume. It measures the range of services offered by the hospital and reflects the diversity, clinical complexity, and the needs for resources in the population of patients in a hospital.

Ownership (*OWNR*): The type of hospital ownership (e.g., government, nonprofit, and proprietary) affects a hospital's financial constraints and objective function. While proprietary rights theory suggests that for-profit format leads to efficient production, comparative studies exploring the effects of hospital ownership offer conflicting views on which ownership structures might be more efficient and report a wide range of empirical results.

Teaching status (*TEAC*): Healthcare research typically distinguishes between teaching and non-teaching hospitals because of the differences in staffing requirements, performance goals, cost structures, and technology adoption attitudes.

Model Development

We use simultaneous regression models to estimate the effect of EMR status and EMR adoption history on various measures of performance. Specifically, we estimate a system of structural equations by treating all dependent variables to be endogenous to the system and to be correlated with the disturbances in the system's equations. The simultaneous equation approach is appropriate for our study context because it provides more efficient estimates of the regression coefficients. To control for the unobserved individual hospital effect that may confound the EMR adoption and performance relationship, we mean-centered all non-constant variables by each hospital. Thus, we are essentially examining whether deviation from the mean on the input variables is associated with deviation from the mean on the output variables by each hospital.

In full matrix notation, the system of regression equations can be expressed as:

$$Y = ZB + \varepsilon$$

In the above matrix, *Y* and ε are $n \times 1$ vectors, and *Z* represents a $n \times m$ vector of endogenous variables. B is a $1 \times m$ vector. ε represents the potentially correlated error terms among all simultaneous equations. We normalized cost-related and capacity-related measures by taking their logarithm values. Among the categorical control variables, government is the baseline for ownership, northeast region is the baseline for districts, and teaching hospitals are the baseline for nonteaching status.

We use the Stata module *cmp* to perform our analysis. *cmp* has the capability to estimate multi-equation systems in which different equations may have different types of dependent variables. The *cmp* module can be applied to recursive systems of equations and uses a seemingly unrelated regression estimator to maximize a higher order multivariate normal generalization of the likelihood function.*cmp* can also estimate robust standard errors, which standard Stata modules for simultaneous equations do not provide. Since our data contains observations from the same hospital over time, we estimate our models with robust standard errors, which correct for model estimations for observations from the same hospital (Wooldridge, 2002).

The sample is described in details in Table 3 and Table 4. The sample includes hospitals from all four districts in the U.S. The majority of the sample is nonprofit hospitals (68.19%), followed by proprietary hospitals (19.22%), and government owned hospitals (12.59%). A vast majority of the hospitals are nonteaching hospitals (88.32%). With respect to EMR adoption, 50.19% of the hospitals did not implement EMR during our observed period, 39.04% practiced EMR for less than 5 years, and 11.15% accumulated more than 5 years' experience in EMR. On average, hospitals provided a total of 87,957.96 adjusted patient days and 19,181.35 adjusted patient admissions, with the cost per adjusted patient day of $2,721 and the cost per adjusted patient admission of $13,169. The average case mix index was around 1.46. We report correlations between variables in Table 4.

< Insert Tables 3 and 4 about Here>

Regression Results

Table 5 shows the regression results for the simultaneous regression models. We first examine whether EMR adoption history is associated with improved hospital performance. The results provide strong support for Hypothesis 1. Consistent with Hypothesis 1, EMR adoption history has a positive and significant effect on operational outcomes and clinical outcomes. While EMR adoption history has a significant and negative effect on operating cost per day, it does not affect operating cost per admission. We next examine whether EMR adoption history has a stronger association with clinical performance than with operational and financial performance (e.g., Hypothesis 2). Contrary to our hypothesis, we find that experience with EMR systems is associated with greater operational outcomes and financial outcomes than with clinical outcomes. It implies that EMR has a greater potential to improve productivity and reduce cost than to enhance clinical quality. A closer examination of the regression results reveals that the variation in clinical outcomes is explained by transfer adjusted service mix index to a large extent.

Compared with EMR adoption history, the EMR status has considerably smaller effects on hospital performance. Interestingly, our results indicate that EMR adoption history is associated with lower costs per day and higher occupancy rate whereas the EMR status exhibits the opposite effect.

This result seems to reinforce our theoretical argument that it will take time to realize the benefits of EMR. EMR status reflects the upfront financial investments and initial time/effect costs with certain EMR systems. Given that a large portion of hospitals were new to EMR during our observed period, it is reasonable to expect a significant and positive connection between EMR status and operating expenses, likely leading to their insignificant association. From a learning curve perspective, it is also reasonable to expect that the steep learning process may possibly degrade existing efficient and focused processes for an average hospital in our sample (Karahanna, Straub, and Chervany, 1999).

We did not find evidence for economies of scale. Hospitals operating with more beds have worse operational outcomes and financial outcomes. Also, hospital performance varies considerably by region. In general, hospitals operated in the northeast district appear to incur higher operating costs yet deliver quality care and operate more efficiently. The coefficients on hospital ownership and teaching status in our regression models are not statistically significant. This finding implies that the direct effects of ownership and teaching status on hospital performance are indeterminate.

DISCUSSION

Our study performs a rigorous analysis of the effects of EMR on hospital performance that tackles both the time factor of EMR adoption and the breadth of the performance matrices. Our findings provide useful insights about the benefits of adopting EMR to the hospitals.

We observed that EMR does lead to a reduction in labor required for delivering quality healthcare. Research suggests that nurses spend more than 35% of practice time on documentation and less than 20% of their time on patient care (Hendrich, Chow, Skierczynski, and Lu, 2008). The longer physicians practice EMR, the more nurse hours can be released from transcribing notes and dictations. Productivity gain from using EMR accrues not only from the elimination of unproductive nurse time, but also from the increased time spent on direct patient care. By removing the ancillary and support functions, EMR helps address the nursing shortage by improving nurse efficiency (Bolton, Gassert, and Cipriano, 2008).

EMR is also found to increase capacity utilization as measured by the actual usage of licensed beds. By reducing the delays associated with paper-based ordering and reporting of results, EMR can give physicians better access to patients' longitudinal test results and enable them to recommend optimal testing and to facilitate coordination of care (Walker, et al., 2005). By sharing patient charts and medical information with multiple stakeholders including nurses and staff, EMR improves patient safety by reducing duplicate therapies and medication abuse (Miller and Tucker, 2009). A well-coordinated quality care can reduce the length of stay and therefore increase the utilization of licensed beds.

We also observed a moderate effect of EMR adoption history on clinical performance. However, this effect is smaller than the effect of service mix index. Our proposed quality measures are consistent with established clinical best practice guidelines. EMR has the ability to incorporate programs that would identify potentially dangerous drug interactions and allergies, which should greatly reduce the chance of adverse drug events when patients receive vaccinations or antibiotics for heart attack, heart failure, or pneumonia treatments.

The effect of EMR on clinical performance should be contingent on patient mix and treatment complexity. Similar to the notion of a "focus factory" or the strategic service vision, hospitals focused on a narrow patient mix such as chronic pneumonia or coronary artery disease can achieve a high level of coordination and teamwork by following a standardized best practice approach (Arnst, 2008; Heskett, 1986; Skinner, 1974; Theokary & Ren, 2011). For "focus hospitals" that have already been relatively effective in applying established procedures, additional gain in clinical quality might be more difficult to achieve. In contrast, for hospitals that offer a wide range of services and therefore tend to treat larger volumes of patients, clinical performance improvement may be more difficult due to the heterogeneity of treatment effects (i.e., patients vary in response to treatment and in vulnerability to side effects). With EMR systems in place, nurses and physicians can better address the heterogeneity of treatment effects by checking all information pertaining to patient demographics, progress notes, problems, medications, vital signs, past medical history, and immunizations in a single repository. Therefore, hospitals with higher service indexes and a longer EMR adoption history are more likely to improve their clinical quality by aligning their practices with established procedures.

Given that EMR increases facility utilization and improves process quality, it is not surprising to find that EMR adoption history is associated with reduced cost per patient day. This finding has important managerial implications on the effectiveness of clinical treatments (Banker, Conrad, and Strauss, 1986). However, we find no evidence that EMR adoption history is directly associated with improvements in cost per admission. Several explanations may account for the result. First, cost per admission reflects the level of coordination across different units (Milsum, Turban, and Vertinsky, 1973). Hospitals epitomize the definition of a “complex service organization” and provide a wide range of services (e.g., laboratory test, cat scan, therapy, surgery) through multiple and interdependent units (e.g., laboratory, cardiology, radiology, and ICU) that have conflicting priorities regarding what service to provide and at what time (Tucker, Nembhard, and Edmondson, 2007). Although EMR has great potentials in coordinating patient care, it does not address issues such as prioritizing tasks and scheduling conflicts across different units. Second, the widely held perception that length of stay (LOS) is a good surrogate for cost may be incorrect (Taheri, Butz, and Greenfield, 2000). Although physicians and administrators have worked tirelessly to reduce hospital stay, empirical studies show that not all hospital days are economically equal (Arnst, 2008; Taheri, et al., 2000). Indeed, the early phase of care involves expensive diagnosis and intervention, while the final days are essentially recuperative. In addition, discharging patients faster is not equivalent to eliminating the attendant end-of-stay costs. To achieve a shorter LOS, either some treatments (e.g., laboratory tests) must be accelerated or other treatments (e.g., pharmaceuticals) must be continued on an outpatient basis. Therefore, those costs would be shifted rather than eliminated.

CONCLUSION

Implication for Research

Our study makes several contributions. First, by confirming the positive effect of EMR adoption history on hospital performance, our study adds to a growing body of technology-value literature in healthcare research. Our study measures EMR adoption history instead of a binary variable for adoption. Thus, our research moves away from the debate on universally positive or negative performance impact of EMR toward a finer-grained quest for how EMR adoption history affects a hospital’s performance improvement overtime.

Second, we expand extant research on healthcare IT payoffs by developing a theoretically sound and empirically valid link between EMR adoption history and hospital performance. Our analysis approach provides efficient and accurate estimates by addressing the interdependence of various performance measures and by controlling for hospital-specific effect. We found no significant connection between performance and hospital characteristics such as teaching status and ownership types. Although nonprofit hospitals and teaching hospitals are more likely to adopt EMR due to access to greater financial resources and less staff resistance (A. Kazley & Ozcan, 2007), our study shows that hospitals benefit from EMR implementation regardless of their teaching status and ownership types.

Implication for Practice

Our findings are useful for practitioners. Hospitals are under increasing pressure to integrate medical information electronically to provide high quality care while maintaining costs under the strict restrictions. However, the adoption rate of EMR by hospitals has lagged far behind the adoption of enterprise information technology in other industries. In addition to financial constraints and system incompatibilities, a major reason for the low EMR adoption rate by hospitals is the resistance from physicians (Hillestad, et al., 2005; McDonald, 1997). In addition, managers may also hold back from EMR implementation without knowing the future payoffs associated with such investments. A convincing business case of EMR based on rigorous empirical evidence can help alleviate hospital management and phsycians' concerns about adopting EMR. Unfortunately, managers and physicians cannot find much affirmative and representative proof of EMRs' benefits from past research. Previous research has focused on limited performance measures with cross-sectional data and reported mixed findings. Although those studies advance our understanding of EMRs in general, they fail to tell the entire story. As stated by the Institute of Medicine's roundtable on value and science-driven healthcare, the institute is seeking the development of a healthcare system that "is designed to generate and apply the best evidence for the collaborative health care choices of each patient and provider… and to ensure *innovative*, *quality*, *safety*, and *values* in health care". Hence, it is important to assess the impact of EMR on the full spectrum of hospital performance. We take this approach by examining the association between EMR adoption history and the clinical, operational, and financial outcomes in U.S. hospitals. We derived our measurements from multiple national databases and our sample presents one third of short-term acute-care hospitals in U.S. Our results suggest the long term impact of EMR on a wide spectrum of hospital performance measures involving operational, financial, and clinical benefits.

Finally, our research provides additional empirical evidence that a hospital that serves a complex patient pool tend to benefit more from EMR implementation in improving its process quality. Although our sample did not include specialty hospitals, hospitals in our sample show varying levels of service mix from .85 to 2.99. The message is clear: if the hospital process has been deteriorating because of the increase in patient mix or treatment complexity, the process quality can be improved by aligning to established procedures through EMR implementation. But for hospitals focusing on a narrow mix of patient, such improvement may be marginal.

Limitations and Future Directions

Our study has several limitations. The first relates to the choice of hospitals. Because we created our sample by matching hospitals across three different national databases, we had to drop a significant number of hospitals that did not meet our selection criteria (e.g., hospitals that are included in all databases and reported EMR status). Therefore, our final sample only represents approximately one third of U.S. hospital population. Although the characteristics of our sample are quite similar to the hospital population, future studies should explore ways to obtain technology application status from the rest two thirds of hospitals, which would allow us to get a more accurate picture of the impact of EMR on the entire hospital industry.

Second, we were unable to obtain additional observational data on the level to which each hospital in our sample goes to ensure the success of a technology implementation. For instance, we do not have information on the percentage and level of physicians practicing with EMR for each hospital. We attempted to counter this weakness by moving beyond a dichotomous measure of adoption by measuring the adoption history, but there is still considerable variation associated with EMR capabilities across hospitals that we did not control for. Future research should explore other options to collect actual EMR usage information (e.g., conduct observational studies or survey studies). Nonetheless, we still show a significant relationship between EMR adoption history and hospital performance and would expect this relationship to be even stronger after factoring in other covariates not included in our study.

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Table 1: EMR Capabilities for US Hospitals from 2006-2011

Stage	Cumulative Capabilities	2006	2007	2008	2009	2010	2011 Q3 US
Stage 7	Complete EMR; CCD transactions to share data; Data warehousing; Data continuity with ED, ambulatory, OP	.00%	.00%	.30%	1.00%	1.00%	1.10%
Stage 6	Physician documentation (structured templates), full CDSS (variance & compliance), full R-PACS	.10%	.30%	.50%	2.80%	3.20%	4.40%
Stage 5	Closed loop medication administration	.50%	1.90%	2.50%	3.70%	4.50%	7.10%
Stage 4	CPOE, Clinical Decision Support (clinical protocols)	3.00%	2.20%	2.50%	1.30%	1.50%	13.20%
Stage 3	Nursing/clinical documentation (flow sheets), CDSS (error checking), PACS available outside Radiology	18.00%	25.10%	35.70%	49.70%	49.00%	46.10%
Stage 2	CDR, Controlled Medical Vocabulary, CDS, may have Document Imaging; HIE capable	38.80%	37.20%	31.40%	15.40%	14.60%	12.60%
Stage 1	Ancillaries - Lab, Rad, Pharmacy - All Installed	18.90%	14.00%	11.50%	6.70%	7.10%	5.90%
Stage 0	All Three Ancillaries Not Installed	2.70%	19.30%	15.60%	1.50%	1.10%	9.60%

Adapted from U.S. EMR Adoption Model by HIMSS Analytics

Table 2: Prior Work Investigating EMR impact

Authors	Theoretical logic	Sample	Approach	Method	Independent variable(s)	Dependent variable(s)	Sign of impact	Conclusion
(Gonzalez-Heydrich, et al., 2000)	EMR can improve communication, coordination of care and clinical outcome	An EMR system in a pediatric clinic	Quantitative	Cumulative and summary statistics	EMR implementation	Utilization and family acceptance	+	Majority parents thought the use of the computer system is a 'good' thing and made it easier to work with the doctor
(Barlow, et al., 2004)	Document the economic benefits of EMR implementation using expenditure data	Expenditure data on EMR	Quantitative	Cumulative and summary statistics	EMR implementation	Savings in transcription, records, and reimbursement	+	Cumulative savings of more than $8.2 million over the next five years
(R. H. Miller & Sim, 2004)	Quanlitative interviews with phyisicans on their use of EMRs	90 interviews with physicians and EMR managers	Qualitative	Interviews	NA	EMR usage	-	1. Quality improvement depends heavily on physicians' use of EMR 2. Identify key barriers for EMR uses including initial cost, omplementary changes, lack of support
(Hillestad, et al., 2005)	Exploratory investigation on potential savings and costs of EMR adoption based on secondary data	Databases from HIMSS, AHA, MEPS, HCUP	Quantitative	Spreadsheet modeling	EMR implementation	Efficiency savings	+	Effective EMR implementation could lead to annual savings of $81 billion
(Walker, et al., 2005)	Model cost-benefit based on published evidence and expert opinion	Literature reviews, expert interviews, and estimates by an expert panel.	Qualitative /Quantitative	Cost-benefit model through Analytica software	NA	Value	+	Fully standardized electronic health care information exchange and interoperability could yield a net annual value of $77.8 billion
(Sidorov, 2006)	Literature review discussing unlikely benefits of EMR implementation	Extant studies	Qualitative	Literature review	EMR implementation	EMR/HER outcome	-	1. Implementation of EMR/HER can lead to greater cost, inconsistent quality, and unchanged malpractice 2. Yet it enables group decision making, open access, outcome responsiblities, and chronic disease management

(Kazley & Ozcan, 2009)	A change in structure to EMRs will likely influence the processes and outcomes of care, including efficiency.	Databases from AHA, HIMSS	Quantitative	DEA	FTEs, bed size, capital assets, operating expenses	Case mix adjusted admissions and outpatient visits	-	1. Only small hospitals may benefit in the area of efficiency through EMR use 2. No significant increase in efficiency over time associated with EMRs
(Queenan, et al., 2011)	IT uses and competitive processes linkages	806 hospitals in US	Quantitative	OLS and hierarchical regression	CPOE use, IT infrastructure	Patient satisfaction	+	1. Positive connection between extent of CPOE use and patient satisfaction 2. IT infrastructure substitutes for CPOE use in its effect on patient satisfaction
(M. F. Furukawa, et al., 2010a, 2010b; Furukawa, et al., 2011)	Electronic medical records (EMR) have the potential to improve nursing care in the hospital setting.	3,048 medical/surgical units in 509 acute care hospitals in US, database from HIMSS and NDNQI.	Quantitative	Fixed effect OLS	EMR implementation	Nurse staff, skill mix, contract percent, patient outcomes	-	1. EMR implementation improve nurse productivity and therefore reduces demand for nurses 2. EMR implementation is not directly associated with improvements in nurse-sensitive patient outcomes

Table 3: Sample Hospital Characteristics

Hospital Characteristics		Count	Percentage
Region			
	North East	716	19.77%
	Middle West	739	2.40%
	South	1,428	39.43%
	West	739	2.40%
Teaching Status			
	Teaching	423	11.68%
	Nonteaching	3199	88.32%
Ownership			
	Government	456	12.59%
	Nonprofit	2470	68.19%
	Proprietary	696	19.22%
EMR Status			
	Implemented	1804	49.81%
	Not Implemented	1818	5.19%
EMR History			
	0 yr	1804	49.81%
	1-5 yrs	1079	39.04%
	6-10 yrs	395	1.9%
	> 10 yrs	9	.25%

Table 4: Descriptive Statistics and Correlation

Variable	Mean	Standard Deviation	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Cost Per Day (LN)	$2,721	$3,615	1												
2. Cost Per Admission (LN)	$13,169	$11,238	.373***	1											
3. Efficiency	22.48%	2.55%	.047	-.335***	1										
4. Occupancy	10.34%	61.31%	-.277***	-.294***	.333***	1									
5. Heath Attack	94.85%	6.22%	.032	.069*	.023	-.020	1								
6. Heart Failure	89.23%	8.50%	.000	.022	-.011	-.001	.409***	1							
7. Pneumonia	91.84%	5.12%	-.041	-.068*	.067*	.027	.310***	.539***	1						
8. Case Mix	1.46	.26	.084***	.211***	-.071**	-.056*	.336***	.212***	-.035*	1					
9. Staffed Beds (LN)	248.09	172.83	.050*	.162***	-.135***	-.101***	.230***	.118***	-.075**	.582***	1				
10. Full Time Employees (LN)	1426.78	1408.41	.079***	.203***	-.041	.039	.202***	.094***	-.105***	.525***	.805***	1			
11. Teaching Status	11.68%	32.12%	.048*	.164***	-.006	.021	.116***	.053*	-.131***	.357***	.439***	.218***	1		
12. EMR History	2.07	2.55	.027	-.021	-.001	.014	.069**	.069**	.011	.133***	.192***	.181***	.153***	1	
13. EMR Status	.502	.498	.031	-.031	-.005	.011	.059*	.044	-.007	.079**	.154***	.543***	.108***	.808***	1

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5: Simultaneous Regression Results

		Cost Per Day	Cost per Admission	Efficiency	Occupancy Rate	Heart Attack	Heart Failure	Pneumonia
Intercept		-.0168**	-.0097	.0211**	.0132	.0001	-.0005	-.0004
Bed Size		.1602**	.1064	-.5918***	-.3579***	-.0056	.0054	-.0006
Full Time Employee		-.0157	-.0319	.0407	.0206*	-.0013	.0062	.0026
Transfer Adjusted Service Mix Index		-.0049	-.0386	.1690	.0114	.0264*	.1027***	.0622***
EMR Dummy		.0868*	.0268	-.0525	-.0411**	.0040	.0107*	.0030
EMR History		-.0612*	-.0024	.0474*	.0445***	.0076***	.0214***	.0146***
Ownership								
	Government	-	-	-	-	-	-	-
	Nonprofit	-.0054	.0018	.0028	.0021	.0003	.0010	.0004
	Proprietary	.0108	-.0021	-.0061	-.0068*	.0004	.0013	.0007
District								
	North East	-	-	-	-	-	-	-
	Middle West	.0092	.0028	-.0084	-.0054*	-.0001	-.0002	-.0003
	South	.0112*	.0074	-.0085	-.0065**	.0003	.0003	.0003
	West	.0135**	.0073	-.0188*	-.0101***	-.0001	-.0004	.0004
Teaching Status								
	Non-Teaching	-	-	-	-	-	-	-
	Teaching	.0048	-.0015	.0078	.0026	-.0004*	-.0001	-.0002
Adjusted R^2		.0145	.0037	.0673	.1334	.0255	.1637	.1937
Root MSE		.2343	.2107	.2027	.0829	.0312	.0349	.0203

* $p < .05$, ** $p < .01$, *** $p < .001$.