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U.S. hospital efficiency and adoption of health information technology

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Abstract This study empirically examines the association between hospital inefficiency and the decision to introduce electronic medical records (EMR) and computerized physician order entry (CPOE) in a national sample of U.S. general hospitals in urban areas in 2006. The main research question is whether the presence of hospital cost inefficiency or other factors driving inefficiency in the production process of a hospital explain low adoption rates of health information technology (HIT) in a hospital setting. We estimated a logistic regression of HIT adoption as a function of hospital cost inefficiency scores obtained using a stochastic frontier analysis. The results demonstrate that hospitals with a greater degree of cost inefficiency were more likely to introduce EMR, suggesting that the benefits of EMR implementation in terms of improved efficiency were likely to outweigh the costs of adoption compared to hospitals that are more efficient. The results showed no association between cost inefficiency and the CPOE adoption decision.

Keywords Health information technology · EMR · CPOE · HIT adoption · Hospital inefficiency · Cost

1 Introduction

Given substantial growth in health care spending, policy makers are on a constant lookout for cost-cutting strategies [1, 2]. While the introduction of health information technology (HIT) is a commonly cited approach to contain costs and improve the quality of care [3–8], several studies predict a slow transition to the era of a digital health care system [9, 10]. Cost remains the biggest barrier to HIT introduction [11]. However, the costs and benefits of implementation may vary across hospitals and may depend on certain hospital characteristics and the hospital's environment [12]. The question we raise in this study is whether hospital inefficiency relates to the decision to implement HIT. The most inefficient hospitals may have the greatest potential for overall cost reduction and benefit improvements; however, such hospitals may have the greatest difficulty in adopting HIT because of the high cost of adoption. This study provides timely insights into the effect of hospital inefficiency on HIT adoption, such as electronic medical record (EMR) and computerized physician order entry (CPOE).

There are a number of factors influencing HIT adoption among hospitals, which can be grouped into hospital characteristics and environmental factors [12]. Hospital characteristics, such as economies of scale, payer mix, ownership, urban or rural location, financial performance, and teaching status are found to be strong predictors of technology adoption [13–19]. Investigated environmental factors include competition, reimbursement policies [20, 21], managed care penetration [22, 23], insurance market characteristics [24], and the technology adoption behavior of neighboring hospitals [12].

In this study, we construct a conceptual model and test hypotheses about whether hospital cost inefficiency enters into the decision-making process of HIT adoption. In the perfectly competitive environment, firms operating inefficiently should go out of business in the long-run, however, health care markets suffer from market imperfections,

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allowing inefficient hospitals to survive [25]. Thus, inefficiency analysis of U.S. hospitals has received much attention in the literature, using mainly data envelopment analysis (DEA) and stochastic frontier analysis (SFA) [25–28]. Both approaches measure inefficiency as the difference between optimal and actual performances. Using SFA, several studies investigated the relationship between inefficiency and several measures of hospital outcomes [25]. Deily and McKay (2006) and McKay and Deily (2008) introduced an inefficiency term as a covariate to explain hospital health outcomes and found a positive relationship between cost-inefficiency and mortality rate in hospitals located in Florida, but not for the entire nation [29, 30]. Deily, McKay, and Dorner (2000) found that high cost-inefficiency was strongly associated with a greater likelihood of non-government-owned hospital closure; while Frech and Mobley (2000) reported that cost-inefficiency was negatively correlated with future growth [31, 32].

Furukawa, Raghu, and Shao (2010) examined the impact of EMR adoption on hospital cost-inefficiency in medical-surgical units and found that the presence of an EMR was associated with significantly higher inefficiency [33]. Their analysis did not model the EMR adoption decision, rather they treated EMR as an explanatory variable in the analysis of cost inefficiency. Kazley and Ozcan (2009) examined the relationship between hospital EMR and efficiency change over time by comparing hospitals with and without EMR and found no improvement in efficiency over time [34]. We contribute to this literature by modeling HIT adoption decision and hypothesizing that hospital inefficiency may enter into the hospital decision to invest in HIT.

2 Conceptual framework

Following the previous literature, we assume that a hospital chooses a set of inputs that will minimize the costs of production given a certain level of output [30]. The production process, described by a production function, converts inputs, such as medical and non-medical personnel, buildings, and equipment, into a given level of output, such as the number of discharges and outpatient visits. Previous research has demonstrated, however, that on average, hospitals do not reach minimum costs, suggesting the presence of some inefficiency in the production process. Given the highly decentralized nature of hospitals, with multiple specialized departments within each hospital, the presence of inefficiencies is not surprising. Thus, HIT adoption has been proposed as a means of cost reduction and efficiency improvement [3, 8, 30].

Any investment decision, including investment in HIT, requires comparing potential future benefits with the costs of investment. The potential benefit of HIT adoption is equal to the current and future reduction in cost and improvements in quality and efficiency. Since HIT adoption has the greatest potential for efficiency improvement among the most inefficient hospitals, the benefits of HIT adoption are likely to be positively related to the degree of inefficiency. The cost of adoption is unlikely to be decreasing with the level of inefficiency or to be constant across all levels of inefficiency. While there is no literature connecting inefficiency to the cost of HIT adoption, the same factors in the production process that create inefficiency are likely to create some obstacles to HIT adoption as well. Thus, HIT adoption is found to lead to loss of productivity for some hospitals at least temporarily [8, 35–38]. For more inefficient hospitals, loss of productivity is likely to last longer. Poon et al (2004) found that physician resistance to CPOE adoption was one of the most significant barriers to adoption. Loss of productivity and "physician rebellion" represent indirect costs of HIT adoption in addition to fixed and quasi-fixed costs, such as costs of installing and maintaining the system and training personnel. Such indirect costs of adoption can be overcome by strong leadership and the ability to leverage hospitalists that are likely to be related to hospital efficiency as well [35]. Therefore, it is reasonable to assume that the costs of adoption are rising with the level of inefficiency. Given both rising costs and rising benefits of HIT adoption, it is unclear whether we should see higher adoption rates among efficient compared to inefficient hospitals or vice versa. Figure 1 demonstrates five possible scenarios. In the first three scenarios, both the benefits and costs of HIT adoption are rising. However, in panel (A), costs are lower than benefits at the low level of inefficiency, while rising faster than benefits as inefficiency increases. In panel (B), the reduction in future costs are small relative to the adoption costs for efficient hospitals, with benefits rising faster than costs as inefficiency rises. In panel (C), benefits are always above costs. A fourth unlikely scenario is when costs are always greater than benefits (not shown).

Given that the effect of hospital inefficiency on costs of adoption has not been addressed in the previous literature, the last two scenarios (D) and (E) consider the case where the costs of HIT adoption consists of only direct costs, such as installation, maintenance, and training costs, and can be represented as a flat curve with respect to the hospital cost inefficiency.[1] In practice, hospitals are unlikely to be able to distinguish between scenarios (D) and (E) since the direct costs of adoption are known and

[1] The authors would like to thank an anonymous referee for suggesting we consider a flat cost curve.

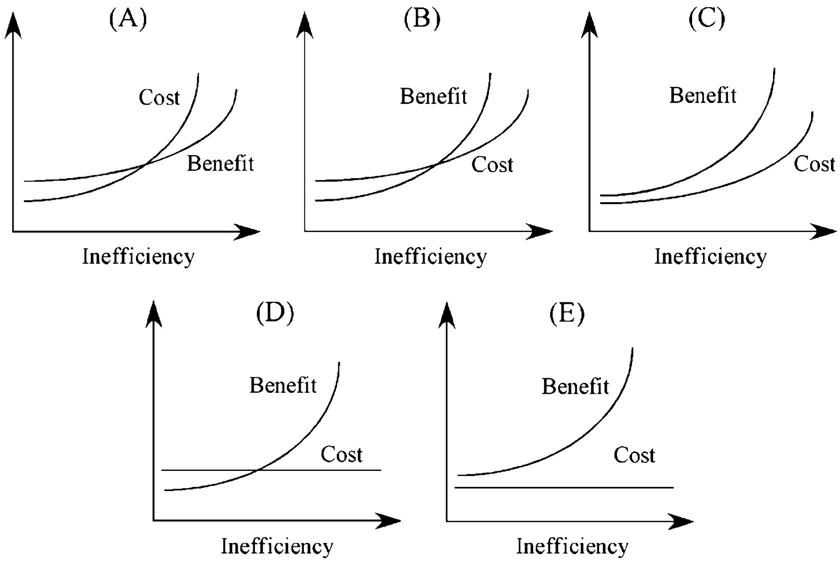

Fig. 1 Conceptual framework: costs and benefits of HIT adoption as a function of hospital inefficiency

provided by the vendors of HIT technology, while some benefits of HIT are uncertain and realized only in the future [8, 35]. However, in both cases the difference between the benefits and costs of HIT adoption, measured by the distance between the flat cost curve and the increasing benefit curve, are greater for more inefficient hospitals, so that more inefficient hospitals have greater incentives for HIT adoption.

Based on this conceptual model, we can derive testable hypotheses. In case (A), we should observe a greater likelihood of HIT adoption among less inefficient hospitals. In cases (B), (D), and (E), we should observe a greater likelihood of HIT adoption among more inefficient hospitals. Scenario (C) will lead to adoption rates that are similar regardless of the level of inefficiency. Thus, the role of cost-inefficiency in the decision to implement HIT is largely an empirical question. Our competing hypotheses are as follow:

Hypothesis 1 (Scenario A) less inefficient hospitals are more likely to adopt HIT, all else being equal;

Hypothesis 2 (Scenario B, D, and E) more inefficient hospitals are more likely to adopt HIT, all else being equal;

Hypothesis 3 (Scenario C) hospital efficiency is not related to the decision about HIT adoption, all else being equal.

Recommendations and government policies for HIT adoption may depend on the scenario that is actually observed. In the case of panel (A), government subsidies for inefficient hospitals will increase the HIT adoption rate. Scenarios (B), (D), (E) suggests offering government subsidies to efficient hospitals, as there are some positive externalities from having HIT across all hospitals that are not internalized by individual hospitals. In the case of panel (C), no government intervention is needed.

3 Data, variables, and methods

3.1 Data and sample

The primary sources of data for the hospital-level analysis come from the Annual Survey of Hospitals provided by the American Hospital Association (AHA) and the Medicare Cost Reports provided by the Centers for Medicare and Medicaid (CMS). The AHA data is considered a near census of U.S. hospitals, providing detailed information on hospital characteristics. The CMS data provides financial characteristics and output measures of hospitals that receive payments from CMS. The data for HIT usage comes from the Health Information Management Systems Society (HIMSS) Analytics Database that includes nearly all non-federal hospitals. In addition, CMS provides Hospital Compare quality measures that describe how well hospitals provide recommended care to their patients. Process of care measures were used as a proxy for the overall quality in U. S. hospitals [39]. All these datasets are commonly used in the analysis of U.S. hospitals.

The sample consists of all acute care general hospitals located in urban areas that have valid and complete information in the Cost Report data and the AHA survey in 2006, and complete HIMSS data in 2006 and 2008. We excluded hospitals with extremely high and low prices of capital and labor (the 1st and the 100th percentiles) from the analysis. The final sample consists of 1,544 hospitals. Sample derivation is presented in Table 1.

Table 1 Sample derivation

Criteria:	N of obs.
Hospital information in the AHA 2006 matched with Medicare Cost Reports 2006	6,047
General acute care facilities only	4,627
Urban U.S. hospitals only	2,287
HIMSS data is available in 2006	2,039
HIMSS data is available in 2008	1,970
U.S. hospitals with valid prices of labor and capital (the 1st and the 100th percentiles are excluded from the analysis)	1,676
All variables are non-missing	1,544

3.2 Empirical strategy

Based on the conceptual model, we expect a hospital to introduce HIT if the expected benefit of HIT adoption is greater than investment costs. That is,

$$\Pr[HIT = 1] = \Pr[Benefit - Cost > 0]$$

Since we cannot measure the expected benefits and costs of HIT adoption directly, we estimate a reduced-form model of HIT adoption as a function of hospital characteristics that influence costs and expected benefits, including hospital cost inefficiency. However, HIT implementation is a process rather than an event and it may take from one to two years from the moment of signing a contract with a vendor to having an operational system [17, 40]. In addition, the implementation process can temporarily cause a short-term loss of efficiency due to the learning and adjustment processes [37]. Figure 2 demonstrates a hypothetical example, in which Hospitals A and B make a decision about HIT adoption in 2006. Hospital A may decide not to introduce HIT since the potential benefits can be smaller compared to the costs, given that Hospital A is already on the path to be more efficient without additional interventions. Hospital B, the more inefficient hospital, may decide to introduce HIT as a means of reducing inefficiencies in its operations. The HIT adoption process takes about 2 years and leads to a temporary loss of efficiency by 2008. At the end, the investment decision was successful for Hospital B and led to a reduction of inefficiencies comparable to the level of the more efficient Hospital A. Based on the empirical strategy presented in Fig. 2, we used a 2-year lag between an outcome variable and covariates that allows modeling the HIT adoption decision as a function of hospital characteristics at the point in time when the decision is made and, most importantly, before hospital performance has been affected by the HIT adoption. Particularly, we are interested in the probability of HIT adoption in a period $t+2$ conditional on not having HIT in a period t as a function of hospital cost inefficiency in period t:

$$\begin{aligned}\Pr[HIT_{it+2} = 1 | HIT_{it} = 0; CostInef_{it}, Controls_{it}] \\ = F\left(\beta_0 + \beta_1 CostInef_{it} + \sum_s \beta_s Controls_{sit}\right)\end{aligned}$$

where HIT_{it+2} and HIT_{it} are binary variables that indicate the presence of HIT in a hospital i at time $t+2$ and t respectively; $CostInef_{it}$ is a measure of cost inefficiency for a hospital i at time t, $Controls_{sit}$ are a hospital's i characteristics s at time t, and $F(*)$ is the cumulative logistic distribution. The benefit and cost of adoption are expected to rise with cost-inefficiency, thus, β_1 measures a reduced effect. Finding $\beta_1>0$ would support the hypothesis that more inefficient hospitals have a greater benefit from

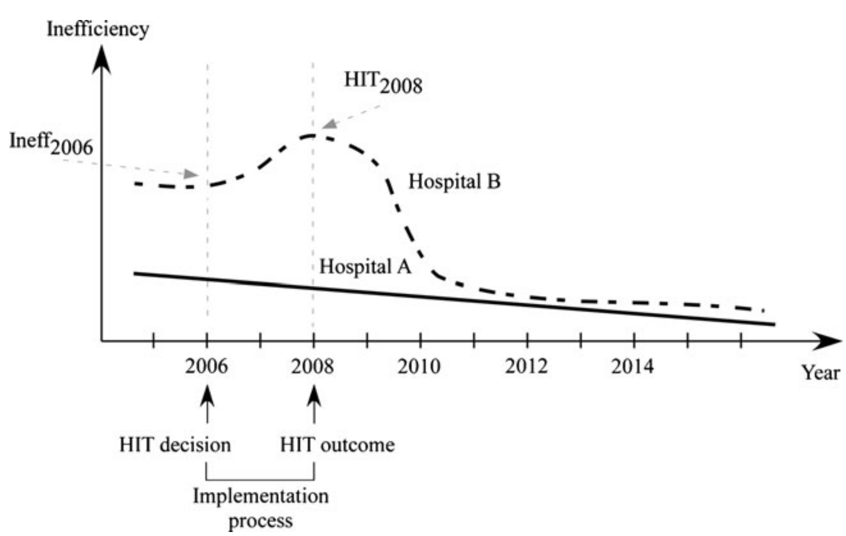

Fig. 2 Empirical strategy: HIT adoption as a function of hospital inefficiency, a hypothetical example

HIT adoption compared to the cost of investment, consistent with the scenarios (B), (D), and (E); while $\beta_1<0$ would be consistent with the hypothesis that inefficient hospitals may experience high HIT adoption costs that outweigh the benefit of adoption demonstrated in panel (A).

Defining HIT is challenging since HIT can be composed of multiple administrative and clinical applications that may vary across different hospitals [41]. Our measure of HIT adoption is the presence of an enterprise electronic medical record (EMR) and computerized physician order entry (CPOE) as reported in the HIMSS Analytics survey. We considered a hospital to have an EMR if its status was "Live and Operational" for the enterprise EMR variable in the HIMSS data. Any other status was coded as not having an EMR. The other status indicators are "Contracted/Not Yet Installed," "Installation in Process," "Not Automated," "Not Reported," "Not Yet Contracted," and "To be Replaced." We did not code "To be Replaced" as having an EMR because there is no indication of whether the system to be replaced is a live and operational enterprise EMR. We created the CPOE variable in the same way. These two applications are commonly used as measures of HIT adoption in hospitals [42–44].

Cost inefficiency is the primary independent variable of interest. As discussed in detail below, we derive our measure of cost-inefficiency using Stochastic Frontier Analysis (SFA). The set of other explanatory variables, $Controls_{sit}$, influencing HIT adoption includes teaching status, ownership, system membership, hospital size, and payer mix. Teaching status is measured by two binary variables—one variable for being a member of the Council of Teaching Hospitals (COTH) and the other for having a medical school affiliation reported to the American Medical Association, but not a COTH member. Hospital ownership is measured by two binary variables for government-owned and investor-owned (for-profit) hospitals, with non-for-profit being an excluded category. System membership is a binary variable that indicates if a hospital has a joint ownership with another organization.[2] Hospital size is measured by the set of binary variables indicating a different number of staffed beds grouped into different categories, such as 1–99, 100–199, and 200–299 beds with 300 and more beds as a reference category. Payer mix is described by the number of Medicare discharges as a percent of total discharges and the number of Medicaid discharges as a percent of total discharges. Hospitals are assigned to three different quintiles based on the values of Medicare and Medicaid shares. Since adoption of CPOE is often preceded by the adoption of EMR, the presence of EMR is also introduced as an explanatory variable in the model describing CPOE adoption.

3.3 Measure of hospital inefficiency

The primary explanatory variable for the model of HIT adoption is hospital cost-inefficiency, $CostInef_{it}$, derived applying the stochastic frontier model to the analysis of the cost function of U.S. hospitals [30, 46–48]. While the derived measure of inefficiency depends on the choice of cost function, the distributional assumption about the inefficiency term, the choice of variables entering the cost function, and the type of data, Rosko and Mutter (2008) found that derived inefficiency scores are robust across different assumptions and specifications of the cost function.[3] Since the Cobb-Douglas function is nested in the translog function, we estimated the following translog cost function[4]:

$$\begin{aligned}
\ln\left(\frac{TC_{it}}{Pl_{it}}\right) &= \alpha_0 + \alpha_1 \ln DISCH_{it} + 0.5\alpha_2 \ln DISCH_{it}^2 \\
&+ \alpha_3 \ln OPV_{it} + 0.5\alpha_4 \ln OPV_{it}^2 \\
&+ \alpha_5 \ln\left(\frac{Pk_{it}}{Pl_{it}}\right) + 0.5\alpha_6 \ln\left(\frac{Pk_{it}}{Pl_{it}}\right) \ln\left(\frac{Pk_{it}}{Pl_{it}}\right) \\
&+ \alpha_7 \ln\left(\frac{Pk_{it}}{Pl_{it}}\right) \ln DISCH_{it} + \alpha_8 \ln\left(\frac{Pk_{it}}{Pl_{it}}\right) \ln OPV_{it} \\
&+ \alpha_9 \ln DISCH_{it} \ln OPV_{it} + \sum_m \beta_m \Pr oductMix_{mit} \\
&+ \sum_f \beta_f Quality_{fit} + v_{it} + u_{it}
\end{aligned}$$

where TC_{it} represents the total cost for hospital i at time t that is normalized by the price of labor Pl_{it}; $DISCH_{it}$ is a number of discharges; OPV_{it} is a number of outpatient visits; Pk_{it} is a price of capital that is normalized by the price of labor Pl_{it}. Following previous studies, product mix descriptors, $ProductMix_{mit}$, and quality measures, $Quality_{fit}$, entered the cost function in addition to input prices and outputs that reflected output heterogeneity across hospitals [28]. The error term consists of two components: v_{it} is random component and assumed to be normally distributed with zero mean and some standard deviation; and u_{it} is a

[2] Kazley and Ozcan (2007) examined the relationship between EMR presence and system types that were developed by Bazzolli and her colleagues [45] rather than system membership. However, about one third of our sample did not have information about system type. Estimation of an alternative specification of our model with a set of binary variables describing system types with missing system type as the omitted category did not alter our results. None of the binary variables describing system types were significant in the EMR adoption model. In the CPOE adoption model, "centralized physician/insurance health system" and "moderately centralized health system" were associated with a lower likelihood of CPOE adoption compared to hospitals with missing type.

[3] Rosko and Mutter (2008) provide an outstanding overview of empirical issues related to the SFA approach for hospitals.

[4] We tested whether the Cobb-Douglas functional form was preferred over the more flexible specification of cost function and found that both Wald and likelihood-ratio tests supported the translog functional form.

measure of cost inefficiency describing the difference between minimum total costs possible for a given level of output and prices and the actual total costs. The inefficiency term, u_{it}, may follow different distributions, including half normal, truncated normal, and exponential. However, convergence assuming a truncated at zero normal distribution could not be achieved. Inefficiency estimates assuming an exponential distribution were highly correlated with estimates assuming a half-normal distribution. The correlation between inefficiency scores estimated under exponential and half-normal distributional assumptions was 0.96. The estimated association between the inefficiency score and the likelihood of HIT adoption was robust with respect to distributional assumptions about the inefficiency term. Thus, the inefficiency term was assumed to have a half-normal distribution for the final results. Based on the estimates of the cost function using SFA, we derived inefficiency scores following Jondrow et al (1982) [49]. Inefficiency scores take values between 0 and 1 and indicate by what percent actual costs were higher than the frontier. We multiplied the inefficiency score by 100 to simplify interpretation of the results in the HIT adoption model.

Total expenses, the price of labor and the price of capital are expressed in 2007 dollars. The number of discharges was adjusted using the Medicare case-mix index. The price of labor is measured by the ratio of total annual salaries divided by the number of full-time equivalent employees. The price of capital is measured by the ratio of total capital related expenses, such as depreciation and interest expenses, divided by the number of beds. Product mix descriptors included percent of ER visits and percent of outpatient surgeries as of total outpatient visits. Quality-related measures included teaching status, accreditation by the Joint Commission on Accreditation of Health Care Organizations (JCAHO), the presence of a cancer program approved by the American College of Surgeons, and four Hospital Compare quality measures reported by CMS (percent of heart attack patients given beta blocker at arrival, percent of heart failure patients given discharge instructions, percent of pneumonia patients assessed and given pneumococcal vaccination, and percent of surgery patients who received preventative antibiotic(s) 1 h before incision) [28, 30].[5]

According to the Hausman test, the price of labor, price of capital, number of discharges, and number of outpatient visits cannot be treated as exogenous and therefore need to be instrumented. Since each endogenous variable enters the cost function non-linearly and interacts with other variables, every non-linear term of endogenous variables and each interaction term have to be treated as separate endogenous variables and have to be instrumented as well. Otherwise, ignoring the non-linearity and interactions of endogenous explanatory variables leads to the estimation of the "forbidden regression" [50]. In this case, the proper treatment of endogeneity requires instrumenting most of the right-hand side variables using a significant number of appropriate instrumental variables. However, some of the instrumental variables used in the past [30, 46, 47] were found to be unsatisfactory.[6] We applied the IVREG2 routine in Stata/SE 11.1 to our cost equation [51, 52] to test the validity of our instruments and found that our model did not pass overidentification and weak identification tests.

In such circumstances, using an instrumental variables approach (with weak instruments), coefficient estimates may be severely biased, and estimation by OLS may demonstrate less bias and so be preferred. [50, 53].[7] Accordingly, we estimated the final inefficiency score for the HIT adoption model without instrumenting endogenous variables in the cost function [30]. While our estimates are potentially biased in the presence of endogenous variables, we were unable to hypothesize about the direction and size of the bias in the presence of multiple endogenous variables and their interactions.

4 Results

Table 2 reports summary statistics for the sample of urban acute care general hospitals in the U.S. in 2006. Characteristics of our sample are similar to what have been reported in the previous studies [30, 46]. About 40% of all hospitals report having an enterprise EMR in 2006, while only 14.1% of all hospitals report having CPOE. The number of hospitals having CPOE almost doubled over the 2-year period, while slightly more than half of the sample reported having enterprise EMR by 2008. We find that on average, hospitals

[5] The Centers for Medicare and Medicaid Services reported 22 Hospital Compare quality measures for calendar year 2006. For some hospitals, not all quality measures were available due to limitations of the data that was used to derive these measures. In addition, quality measures were highly correlated with each other. We chose one measure from each condition category, such as acute myocardial infarction, congestive heart failure, pneumonia, and surgical care, based on the largest number of observations available for each measure and the highest correlation with other quality measures within each condition group.

[6] Previously used instruments: population, per capita income, and unemployment rate at the county level and a set of binary variables describing urban location, type of ownership, state, and year.

[7] Despite the presence of endogenous variables in the cost function, it is still unknown in the literature whether bias present in the coefficients could be transmitted to the inefficiency estimates. That is, it is possible that a bias could occur in the coefficients but not be transmitted to the inefficiency estimates. Thus, derived efficiency measures may still be valid (personal communication with William Greene, Toyota Motor Corp. Professor of Economics, Leonard N. Stern School of Business, New York University).

Table 2 Descriptive statistics for the sample of U.S. hospitals, 2006

Variable:	Description:	Mean	S.D
HIT Variable:			
EMR in 2006	1=yes, 0=no	0.409	0.492
EMR in 2008	1=yes, 0=no	0.520	0.500
CPOE in 2006	1=yes, 0=no	0.141	0.348
CPOE in 2008	1=yes, 0=no	0.270	0.444
Inefficiency score, (%)	Score derived from the SFA*100	15.85%	7.17%
HIT Adoption:			
COTH member	1=member of Council of Teaching Hospitals, 0=no	0.131	0.338
Teaching, other	1=medical school affiliation but not COTH member, 0=no	0.408	0.492
Government ownership	1=yes, 0=no	0.115	0.319
For-profit	1=yes, 0=no	0.188	0.391
System membership	1=yes, 0=no	0.661	0.474
N of staffed beds	Number of staffed beds	294	207
% Medicare	(Medicare discharges/Total discharges)*100	36.32	12.12
% Medicaid	(Medicaid discharges/Total discharges)*100	14.37	11.64
Additional variables for the SFA Analysis:			
Total expenses, ($)	Total expenses during the reported period	2.4E+08	2.4E+08
Price of labor, ($)	Total annual salaries /FTE employees	55,655	9,944
Price of capital, ($)	(Depreciation+interest expenses)/N of beds	44,458	26,902
N of discharges	N of discharges	13,905	10,388
N of outpatient visits	Total N of outpatient visits	215,521	236,376
CMI	Case Mix Index	1.44	0.23
% ER visits	(ER visits/Outpatient visits)*100	29.18	16.72
% Outpatient surgeries	(Outpatient surgeries/Outpatient visits)*100	4.24	3.52
JCAHO	1=accreditation by Joint Commission on Accreditation of Health Care Organizations, 0=no	0.948	0.223
Cancer program	1=cancer program approved by American College of Surgeons, 0=no	0.557	0.497
AMI quality measure	Heart Attack Patients Given Beta Blocker at Arrival	0.927	0.080
CHF quality measure	Heart Failure Patients Given Discharge Instructions	0.694	0.210
Pneumonia quality measure	Pneumonia Patients Assessed and Given Pneumococcal Vaccination	0.734	0.193
Surgery quality measure	Surgery Patients Who Received Preventative Antibiotic(s) One Hour Before Incision	0.823	0.138
Number of observations:		1,544	

exceeded costs at the frontier by 16%, which is consistent with what has been previously reported. Depending on the assumptions made in SFA, Rosko and Mutter (2008) documented average inefficiency scores between 11.59% and 18.82% for a subset of U.S. urban hospitals in 2001.

Table 3 reports the average inefficiency score in 2006 by the presence of HIT in 2008 for the hospitals that do not have HIT in 2006. Since it takes approximately 2 years to fully adopt HIT after the decision to introduce HIT is made [17, 40], we used a lag of 2 years to eliminate the effect of the HIT adoption process on hospital inefficiency. These descriptive results suggest that more inefficient hospitals were more likely to introduce EMR in the future. Interestingly, the CPOE adoption decision appeared to be unrelated to hospital inefficiency; however, this relationship is most likely to be contaminated, as CPOE adoption is preceded by EMR adoption in many cases. About 23% of hospitals that had EMR but not CPOE in 2006 report CPOE by 2008, compared to 11% of those hospitals that did not have EMR in 2006.

Table 3 Average inefficiency score in 2006 by the presence of HIT in 2008 for the U.S. hospitals without HIT component in 2006

Presence of HIT	Yes	No	Difference	p-value
EMR status in 2008 (%)	17.43	15.49	1.94***	0.003
CPOE status in 2008 (%)	14.10	13.78	0.32	0.486

*** —statistically significant at 0.01 level.

Table 4 presents the results for the logit models of EMR and CPOE adoption decisions conditional on not having these components with (Model 1) and without (Model 2)

Table 4 Probability model of HIT adoption for the U.S. hospitals

Variable:	EMR		CPOE	
	(1) OR/[95% CI]	(2) OR/[95% CI]	(1) OR/[95% CI]	(2) OR/[95% CI]
Inefficiency score	–	1.033***	–	1.010
	–	[1.013,1.054]	–	[0.975,1.047]
COTH member	2.018**	2.131**	2.000***	2.006***
	[1.107,3.677]	[1.186,3.828]	[1.181,3.385]	[1.192,3.375]
Teaching, other	0.813	0.835	1.054	1.064
	[0.538,1.230]	[0.552,1.262]	[0.719,1.544]	[0.727,1.556]
Government ownership	0.619	0.538*	0.578**	0.563**
	[0.308,1.246]	[0.276,1.045]	[0.334,1.000]	[0.333,0.950]
For-profit	0.547***	0.582**	0.571**	0.579**
	[0.354,0.845]	[0.370,0.916]	[0.359,0.910]	[0.366,0.915]
System member	0.929	0.918	0.721**	0.721**
	[0.660,1.307]	[0.654,1.289]	[0.526,0.988]	[0.525,0.990]
Hospital size: 1–99 beds	0.610	0.709	1.372	1.427
	[0.285,1.306]	[0.322,1.560]	[0.700,2.689]	[0.716,2.844]
Hospital size: 100–199 beds	0.921	1.001	0.686*	0.701*
	[0.557,1.524]	[0.595,1.683]	[0.469,1.003]	[0.466,1.055]
Hospital size: 200–299 beds	0.983	1.059	1.146	1.164
	[0.587,1.647]	[0.622,1.804]	[0.777,1.691]	[0.780,1.736]
% Medicaid: 0–7.5%	1.325	1.348	1.205	1.213
	[0.858,2.045]	[0.859,2.114]	[0.779,1.866]	[0.784,1.877]
% Medicaid: 16% or more	1.303	1.284	1.147	1.143
	[0.863,1.966]	[0.845,1.950]	[0.778,1.690]	[0.774,1.686]
% Medicare: 0-31%	1.320	1.368	1.247	1.256
	[0.856,2.035]	[0.896,2.088]	[0.864,1.800]	[0.864,1.824]
% Medicare: 41% or more	1.496*	1.421	1.104	1.090
	[0.959,2.332]	[0.918,2.199]	[0.719,1.696]	[0.708,1.678]
EMR present	–	–	2.254***	2.260***
	–	–	[1.544,3.289]	[1.551,3.293]
Constant	0.204***	0.112***	0.133***	0.114***
	[0.111,0.377]	[0.047,0.267]	[0.082,0.216]	[0.055,0.236]
Pseudo R-squared	0.0263	0.0350	0.0625	0.0629
N of observations	913	913	1,327	1,327

*** —statistically significant at 0.01 level; ** — statistically significant at 0.05 level; * —statistically significant at 0.1 level. OR—odds ratio; CI—confidence interval. Logit model. Omitted categories: being non-for-profit, non-teaching, non-system member, 300 or more staffed beds, percent of Medicaid discharges between 7.5% and 16%, percent of Medicare discharges between 31% and 41%, and no EMR present in case of CPOE model.

inefficiency score to demonstrate sensitivity of the estimated models and the predictive power of the efficiency measures. Since the measure of cost inefficiency is derived based on the SFA estimates, the usual standard errors in the logit model can be underestimated. Thus, we estimated bootstrapped standard errors. Estimating Model 1 without efficiency scores, we find that COTH members were more likely to introduce both EMR and CPOE in line with some of the previous studies [16, 17, 54]. For-profit status was associated with a lower likelihood of EMR and CPOE adoption, while government ownership[8] was negatively associated with the likelihood of CPOE adoption. System membership and number of staffed beds between 100 and 200 were negatively associated with the likelihood of

[8] Since HIMSS surveys only non-federal hospitals, government ownership indicates only local government ownership, such as city, county, and state.

CPOE adoption. Hospitals with greater share of Medicare discharges were more likely to introduce EMR. The presence of EMR was strongly associated with a greater likelihood of CPOE adoption.

According to the regression results with inefficiency scores, hospital cost-inefficiency is positively related to the EMR adoption decision, but not CPOE adoption. A one-percentage point increase in inefficiency score was associated with a 3.3% increase in the odds of EMR adoption ($p<.01$). The change in inefficiency score that is equal to the standard deviation of this measure would be associated with about a 24% increase in the odds of EMR adoption. A change in inefficiency score from the 25th percentile to the 75th percentile would be associated with almost 27% increase in the odds of EMR adoption. In the case of CPOE adoption, the inefficiency score appeared to be unrelated to the adoption decision, while the presence of EMR was strongly associated with the subsequent adoption of CPOE.[9] Introducing inefficiency measures to the models of EMR and CPOE adoption had a very small impact on coefficients and standard errors of other explanatory variables. Government ownership became a significant predictor of EMR adoption, while Medicare share of discharges became insignificant, although significance was only marginal in Models 1 and 2 in the case of EMR adoption. However, introducing an inefficiency score significantly improves the goodness of fit, McFadden's pseudo R-squared, for the model of EMR adoption, suggesting a significant role of the inefficiency concerns in the decision making process about HIT adoption in the hospital setting.

5 Summary and discussion

The results of this study document a positive association between hospital cost inefficiency and the likelihood of introducing EMRs. This result supports scenarios (B), (D), and (E) discussed in the conceptual framework, where hospitals that are more inefficient are more likely to introduce HIT as benefits exceed the costs of adoption. Following the conceptual framework, this result suggests that the benefits of EMR adoption are more likely to outweigh the costs of adoption for hospitals with a greater degree of inefficiency. That is, such hospitals may expect a reduction in costs attributed to the inefficiencies in the production process, in addition to a reduction in overall costs attributed to normal hospital operations. Indeed, Borzekowski (2009) finds that HIT adoption led to cost reductions for U.S hospitals between 1987 and 1994 in the long run; however, it is not clear whether reductions occurred in costs associated with inefficiencies in the production process. Thus, further research is warranted to determine the effect of HIT adoption on future costs and cost efficiency improvements.

Contrary to the EMR results, we find no association between hospital cost inefficiency and CPOE adoption. It appears that the decision to implement CPOE may be preceded or accompanied by the decision to adopt EMRs, which could potentially affect the relationship under investigation. We find that the inefficiency score was not associated with CPOE even after an interaction term of inefficiency and the presence of EMR was added to the model. However, few hospitals report having CPOE and not having an EMR, presumably because the benefits of having CPOE are enhanced by the presence of an EMR. We are not aware of any empirical or theoretical work examining the determinants of an HIT application adoption sequence that can provide further insight into the observed results. Further, EMR may be perceived as a means of improving production efficiency while CPOE may be perceived as a means of improving quality more than efficiency. Thus, it is possible that hospitals do not consider inefficiency in their decision to introduce CPOE.

A key policy implication is to offer government subsidies to more efficient hospitals, because they are not as motivated by the potential benefits as are hospitals that are more inefficient, even though there are some positive externalities from having EMRs across all hospitals that are not internalized by individual hospitals. Thus, one of the benefits of HIT adoption is that providers may exchange information about patients, which has a strong potential to reduce unnecessary testing, improve coordination of care and decision making about treatment [55–57]. Given rising health care costs, health information exchange has a strong potential for health care cost reduction overall, while single hospitals may not benefit directly from such systems. Indeed, some evidence exists demonstrating that some hospitals are unwilling to share patient information because of the fear of losing patients to competitors, suggesting that some policy intervention is required to encourage the exchange of data [57]. Since positive externalities have not taken place to the full extent—that is something the federal government is hoping to achieve through the 2009 HITECH Act [57]—it is difficult to provide a more detailed policy proposal. In addition, our study does not provide any evidence for whether costs of HIT adoption are increasing or constant with respect to hospital inefficiency that is

[9] We estimated a separate logit model of CPOE adoption with the interaction term of inefficiency score with the presence of EMR in 2006 to test the hypothesis that previous introduction of EMR could potentially affect the link between inefficiency and the CPOE adoption decision (available from authors upon request). However, the coefficients for the inefficiency score as well as for the interaction term were statistically insignificant. Ppresence of EMR was also insignificant suggesting that small sample size can explain statistically insignificant results.

needed to determine the size of subsidies to stimulate HIT adoption. Several studies demonstrated instability of rankings for individual hospitals across different sets of assumption about the cost function and error terms, representing an additional challenge to the development practical policy recommendations [58, 59]. However, we can still derive some conclusions about hospitals as a group and provide a starting point for policy discussions [30].

This study contributes to the literature investigating the mechanisms motivating the HIT adoption decision and the effect of HIT adoption on hospital performance. Our findings demonstrate that hospital cost inefficiency is likely to have an influence on the decision to adopt EMR in the first place. Therefore, the presence of EMR is a potentially endogenous variable that may lead to bias estimates of the effect of EMR on cost and efficiency found in previous studies. Kazley and Ozcan (2009) hypothesized that hospitals with EMR are more efficient than hospitals without EMR [34]. However, Fig. 2 demonstrates that more inefficient hospitals may use EMR to reduce their inefficiency level comparable to the levels of more efficient counterparts. If so, differences in efficiency levels by the presence of EMR may not exist. Similarly, comparing change in inefficiency levels by the presence of EMR in the post adoption period may not detect any differences if adopting hospitals already achieved reductions in hospital costs inefficiency during later periods as seen in Fig. 2. In addition, EMR adoption may result in higher cost inefficiency during implementation, learning and training stages that may lead to a positive association between HIT adoption and inefficiency that can be mistaken for EMR causing higher inefficiency.

Due to several limitations of our study, results are suggestive and require further investigation. Our measure of inefficiency is based on the SFA approach using endogenous variables. In addition, our analysis was limited to 1 year of data and to the sample of hospitals that did not report having HIT in 2006. The experience of hospitals that adopted HIT prior to 2006 was not considered and is left for future research.

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