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Impact of CPOE Usage on Medication Management Process Costs and Quality Outcomes

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Abstract

We assess the impact of computerized physician order entry (CPOE) systems usage on cost and process quality in the medication management process. Data are compiled from 1,014 U.S. acute-care hospitals that have already implemented CPOE. Data sources include the American Hospital Association, HIMSS Analytics, and the Centers for Medicare and Medicaid Services. We examine the association of CPOE usage with nursing and pharmacy salary costs, and evidence-based medication process compliance. Empirical findings controlling for endogeneity in usage show that benefits accrue even when 100 percent usage is not achieved. We demonstrate that the relationship of CPOE usage with cost and compliance is non-linear.

Keywords

CPOE, HIT, meaningful use, salary costs, quality outcomes

Medication management is a key process impacting cost and quality outcomes in inpatient settings. The process includes prescribing, communicating the order, dispensing, administering and monitoring. Recent legislative developments and managerial innovations have emphasized electronic health records (EHR) as a critical strategic resource to improve outcomes and curb costs related to the inpatient medication management process (Aspden et al. 2006; Varshney 2013). Strong financial and regulatory incentives are also in place for hospitals to increase EHR technology usage in clinical processes (Monheit 2011). However, research on the adoption of computerized physician order entry (CPOE) and other EHR technologies has shown marginal and mixed benefits for medication management (e.g., Appari et al. 2012; Bardhan and Thouin 2013; Encinosa and Bae 2011; Kazley and Ozcan 2008; McKibbon et al. 2012; Patterson et al. 2012; Spaulding et al. 2013). Literature on CPOE systems utilization has mostly observed the effects of usage on quality measures such as process compliance (e.g., Jones et al. 2011) or examined impacts in randomized controlled trials (McKibbon et al. 2012). Few cross-sectional studies of medication management technology have jointly examined quality and cost outcomes associated with use of these technologies.

The purpose of this research is to examine the association of CPOE usage with labor costs and process compliance. We identify CPOE as a critical component of an EHR that enables order entry management and clinical decision-making support. In addition to CPOE, we identify

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advanced Hospital EHR technologies such as decision support and medication administration records to influence usage levels. The research context is highly relevant to understanding the impacts of the Meaningful Use (MU) rule of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009. The first-stage requirements of MU stipulated that at least one medication for 30 percent of patients be ordered using a CPOE system (Centers for Medicaid and Medicare Services [CMS] 2012). The second stage increases this requirement to 60 percent of provider orders. The third and final stage is expected to move the bar up in terms of usage. In this research, we examine the association of CPOE usage with labor costs and compliance with evidence-based process standards. The empirical approach tests for non-linear association of usage with process outcomes.

Hospitals deploy a significant amount of resources on the medication management process. Nursing activities (including administering and monitoring) account for almost half of the costs of direct patient care (Welton 2007). Registered nurses spend approximately 27 percent of their time on medication-related activities (Keohane et al. 2008). Inefficiencies in communication and documentation in one stage of the process often contribute to difficulties in the other stages. Mistakes in prescribing often relate to the fact that health care providers and pharmacists have to sort through enormous amounts of information related to prescriptions. Poor documentation further exacerbates this problem. In 2012, providers had to deal with over forty thousand medications (Mansur 2013). Almost one-third of adults in the United States take more than five medications per week (Aspden et al. 2006). Providers often do not have time to research each medication brought by their patients and all the possible interactions. Dispensing the drug from pharmacy inventory is also prone to error. An observational study found dispensing error rates occasionally as high as 10 percent (Flynn, Barker, and Carnahan 2003). Error rates at administration are likewise high (Barker et al. 2002).

In contrast to the strong support and enthusiasm for encouraging EHR technology use among policy makers, extant literature has demonstrated mixed effects of CPOE and other EHR technologies on efficiency and process compliance (Menachemi and Collum 2011). Seblega (2010) finds that adoption of EHR technology had no significant impact on patient quality indicators; however, adoption had a modestly positive impact on process compliance. In a panel data set from the same time frame, Bardhan and Thouin (2013) confirm the association of EHR technology adoption with process compliance. Similarly, Patterson et al. (2012) find modest increases in process compliance particularly when decision support is present, and Radley et al. (2013) estimate that CPOE usage reduces medication errors by approximately 12 percent. Furukawa, Raghu, and Shao (2010a) find that adoption of medication administration and nursing documentation systems are associated with inefficiencies in the acute-care environment.

Weak outcomes associated with the adoption of CPOE and EHR technologies may be a result of an inherent research assumption of homogeneous adoption and usage of these technologies across hospitals. Many practitioners resist EHR technologies due to usability concerns and their adverse impacts on productivity (McDonnell, Werner, and Wendel 2010). Huerta et al. (2013a, 456) find that in relation to efficiency and productivity, the best EHR implementation "is not to adopt all." They suggest that it may not be profitable to be on the leading edge of adoption of EHR technology. As a result, hospital IT staff may promote EHR technology use in units where they expect high user enthusiasm and least resistance. As usage spreads to other units, it is inevitable to encounter user resistance, work-arounds and other process obstacles.

We expect CPOE usage impacts on process outcomes to be non-linear (Appari, Johnson, and Anthony 2013; Jones et al. 2011). Certain units in the hospital may be more amenable to digitization than others. First, the orders that are well suited to digitization will provide the most benefit for efforts expended to use the system. Orders that are not well suited for digitization may incur more expenses and fewer benefits. Second, not all users are equally adept at using computers. As in any organization, some hospital staff can use new systems with minimal training. Consistent with the theory of diffusion of innovations

(Rogers 1962), these users are likely to be early adopters and have high self-efficacy and tolerance for uncertainty. Early adopters also are capable of utilizing advanced capabilities (such as macros and shortcuts) to improve their productivity. Late adopters need considerable individually tailored training and may also be unlikely to utilize advanced system capabilities. As such, our research design specifically set out to identify any inherent non-linear impacts of usage associated with outcomes.

To empirically assess the impact of CPOE systems usage on cost and process quality in the Medication Management Process, we merge available data from the American Hospital Association (AHA), HIMSS Analytics, and the Centers for Medicare and Medicaid Services. Our findings suggest that CPOE usage impacts may accrue well before the attainment of 100 percent usage. Moreover, the analysis shows that pushing all medication orders through the CPOE system is not likely the optimal solution to reduce costs and increase compliance with evidence-based quality measures. Recognition of this fact is important as the third stage of MU is under development. Furthermore, we show that not all hospitals may be able to effectively attain high usage levels due to endogenous organizational factors.

Literature and Hypotheses

Our conceptual framework is based on the paradigm of structure, process, and outcomes (Donabedian 2002; Furukawa, Raghu, and Shao 2010b). In our conceptualization, management makes decisions about CPOE adoption (structure), which determines the medication management process and results in improvements in outcomes (cost and quality). CPOE and associated EHR technologies automate clinical activities in the delivery of medical care. CPOE systems allow physicians to directly enter orders for medications, diagnostic tests, and ancillary services (Poon et al. 2004). Usage of order entry systems can impact efficiency through medication ordering (Ford et al. 2011) and lab ordering functionality (Huerta et al. 2013b). The main impetus for CPOE usage is to automate alerts and prevent errors in provider orders. Thus, CPOE usage has the potential to improve cost and quality outcomes.

CPOE is an integral and key component of medication management within the hospital. Prior to or at the time of hospital admission, a pharmacist begins the medication reconciliation step to review the current medications, dosage, and any compliance issues. Depending on the sophistication of the EHR, drug interactions, lab interactions, allergy conflicts, and policy deviation alerts may be generated for order sets. These checks are completed every time changes are made to the order set. The attending physician and pharmacist are ultimately responsible for checking for medication issues. Decision support is commonly provided through CPOE and pharmacy components of the EHR system. The entire order set is specified at the beginning of the patient's stay in the hospital with additional changes made as required during treatment and observation.

From a cost and compliance perspective, physician use of CPOE substantially impacts nursing departments and the pharmacy. When changes to the order set are necessary, the prescribing stage of the process begins with the provider ordering a medication for a patient. In an environment without CPOE, providers handwrite the order on a scratchpad or order form. The order is then delivered to the nurse or the administrative staff and is processed. In some cases, those reading the order have difficulty deciphering the provider's handwriting. This necessitates physician callbacks to verify the order. Order verification is costly in terms of employee hours. It is possible that the nurse or other staff skip order verification and simply make their best guess at what the order should be. This can happen when the staff is busy, orders are urgent, physicians are slow returning phone calls, or physicians are annoyed by callbacks. In the electronic environment, the providers enter the order into the computer themselves in a structured format. The computer system performs the initial verification step and can eliminate guesswork and interpretation by staff.

The dispensing stage begins when the order arrives at the pharmacy. As with the prescribing stage, if the order is not legible, pharmacists or pharmacy staff will have to call the physician to verify orders. Furthermore, many pharmacies use scanning or fax equipment to receive orders. In some cases, these scanners and fax machines can produce difficult to read documents. CPOE systems generally overcome this challenge by requiring the provider to enter the order into the computer and then transmitting that order electronically to the pharmacy. Most hospitals with a CPOE system would have also adopted and integrated CPOE with the pharmacy system. If the CPOE system is implemented with decision support for ordering, pharmacists should not have to correct unusual orders or dosages. Furthermore, the system can detect and warn the attending physician of drug, allergy, and lab interactions before the order is sent to the pharmacy. The dispensing stage of the process is completed when the nursing staff receives the medication to be administered.

The administering stage of the process includes order verification, order fulfillment, and record keeping. When mistakes are not caught in the prescribing and dispensing stages, they are occasionally discovered in the administering stage. When nurses receive the orders, they verify the order against patient records, the chart, and other documentation. In worst-case scenarios, the order is discovered to be incorrect after administration when charts are reviewed or when the outcome was negative. When the error is discovered in the administering stage of the process, nursing and pharmacy resources have to be used to track down the problem and correct it. These resources are expensive, to say nothing of the danger to patients.

Although regulators and policy makers expect that CPOE and its associated systems would increase quality (Greenberg, Ridgely, and Bell 2004), findings related to CPOE adoption are mixed. We only discuss a small sample of this research here. Wu et al. (2006) conclude from their meta-analysis that research showing positive outcomes focus on a handful of organizations that have had substantial experience with EHR systems. They also find that the evidence from other organizations is less conclusive. More recently, Wetterneck et al. (2011) find that CPOE implementation increased the number of duplicate orders in the process. Related research on EHR implementation has led to similar findings. Encinosa and Bae (2011) find that EHR technologies do not reduce the number of patient safety events in a hospital; however, EHR technologies are associated with lower mortality, readmissions, and costs after an event occurs. Herrin et al. (2012) find that exposure to EHR technology improved outcomes for diabetes patients. Consistent with our conceptual framework, we frame the following two key hypotheses for our research:

Hypothesis 1: CPOE usage is associated with lower process labor costs.
Hypothesis 2: CPOE usage is associated with improved process compliance.

Predictions based on the theory of innovation diffusion and recent empirical evidence point to the possibility that the relationship between usage and process outcomes is not linear. Theory of innovation diffusion (Bass 1969; Rogers 1962) predicts different costs of bringing physicians onboard with the CPOE. For instance, early adopters of CPOE may be more enthusiastic about changes whereas late adopters may be more resistant (Fichman and Kemerer 1999). Obviously more resources are needed to push resistant users to use the system. A second stream of logic follows economic incentives. Organizations may target initial usage in areas where systems may have the most impact. Jones et al. (2011) analyze the effect of system usage on mortality rates for two different thresholds. They suggest that requirements of MU stage 1 will not lead to decreased mortality rates but that 60 percent use of CPOE for orders would lead to an effect. Appari, Johnson, and Anthony (2013) investigate adoption of EHR systems in response to the MU rule. They show that the adoption of a basic EHR was associated with increases in process compliance; however, adoption of advanced EHR systems was associated with decreases in quality. Given the theoretical backing and recent empirical findings, we propose that CPOE usage impacts will be non-linear.

In developing our research model, we recognize that CPOE usage can be influenced by endogenous factors even when there is no endogeneity in the adoption decision (Appari et al. 2012; Jones et al. 2011). Incentives to use a CPOE system may be higher in organizations that have invested in related medication management technologies such as clinical decision support and Electronic Medication Administration Records (EMAR).

Method

Data

Data for this cross-sectional analysis are taken from multiple sources. Hospital demographic information is taken from AHA 2007 Annual Survey of member hospitals. The 2007 survey included an EHR supplement with questions regarding the percent of patients whose orders were placed through the automated system. Although AHA has continued to provide an EHR supplement to their survey, 2007 was the only year that included the usage variables needed to address the study objectives. The annual survey of the HIMSS Foundation on IT adoption was considered for usage data. However, these data appeared to be less reliable and have many null values. Vendor information for medication management systems is obtained from the HIMSS Analytics database.

Dependent variables for the study comprise salary costs and process compliance. Pharmacy and nursing salary costs are computed from the Centers for Medicare and Medicaid Services (CMS) database. The data related to process compliance with evidence-based medicine (EBM) practices are provided through the CMS-Hospital Compare database. The database provides many measures related to several diagnoses. We use only those measures that the medication management process has the potential to impact. EBM measures are separated into four categories: acute myocardial infarction (AMI), heart failure (HF), pneumonia (PNE), and surgical care improvement and infection prevention (SIP). The combined data set from CMS Cost Reports, HIMSS, AHA, and Hospital Compare consists of a sample of 1,014 U.S. hospitals that have adopted CPOE.

Cost variables used in this analysis are from the pharmacy and nursing cost centers of the hospital. Although, there are other cost centers related to the medication management process, nursing and pharmacy costs are both closely related to the process and a major cost component to the hospital. Nursing salary costs refer to nurses, nurse managers, nurse assistants, and administrative staff on the nursing floors. Pharmacy salary costs refer to pharmacists, pharmacy technicians, pharmacy managers, and related administrative assistants. Yearly salaries are divided by the number of patient days for each hospital. Patient days refers to the sum of the length of stay of all the patients in the hospital for the given time period. Cost variables as well as bed size are highly skewed to the right and are corrected using a logarithmic transformation for analysis.

Sample descriptive statistics are provided in Table 1. The study sample is weighted substantially to larger hospitals because of the need to focus on hospitals that have already adopted CPOE (sample mean = 255 beds, population mean = 155 beds). The sample is also weighted more toward not-for-profit organizations than the general population (sample mean = 71 percent, population mean = 50 percent). Sample payer mix related to Medicare and Medicaid are both within 3 percent of the national average. As could be expected, the sample is also weighted more toward Joint Commission accredited hospitals, members of the Council of Teaching Hospital (COTH), and hospitals with medical school affiliations. The sophistication index is a weighted measure of the procedures available at the hospital. Procedures that are less common are given a heavier weighting. The sample is also weighted toward more sophisticated hospitals by this index.

IT Variables

Four technology variables are used. The first is the key independent variable of CPOE usage. This measure is taken directly from the AHA EHR supplement. The data were generated by the survey item—"Please provide your best estimate for the percentage of inpatients at your hospital for whom medication orders are written electronically." The survey records responses in the following categories of usage: 0 percent, 1 to 25 percent, 26 to 50 percent, 51 to 90 percent, and 91 to 100 percent (see Table 2). The second and third IT variables are calculated using a set of items from the AHA EHR Supplement. They are composite scores related to CPOE decision

Table 1. Summary Statistics.

Variable[a]	*M* (*SD*)
Clinical salary per patient day	\$280 (\$104)
Pharmacy salary per patient day	\$35 (\$28)
Bed size	255 (237)
% payer from Medicare	45 (13)
% payer from Medicaid	18 (11)
Sophistication index	4.51 (2.08)
Ownership	
Government	18.54%
For-profit	10.26%
Not-for-profit	71.20%
Location	
Rural	11.05%
Micro	16.67%
Metro	72.29%
JCAHO	85.90%
COTH member	14.40%
Associated with a medical school	37.87%
Region	
Northeast	20.51%
Southeast	17.26%
South-center	18.34%
North-center	25.94%
Mountain	6.11%
Pacific	9.27%
AMI-related EBM success[b]	94% (8%)
HF-related EBM success[b]	89% (10%)
PNE-related EBM success[b]	87% (8%)
SIP-related EBM success[b]	85% (11%)

Note. Regions are as follows: the northeast region (Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania), the southeast region (District of Columbia, Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia), the south-central region (Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Texas), the north-central region (Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, North Dakota, Nebraska, South Dakota), the mountain region (Arizona, Colorado, Idaho, Montana, New Mexico, Nevada, Utah, Wyoming), and the pacific region (Alaska, California, Hawaii, Oregon, Washington). AMI = acute myocardial infarction; EBM = evidence-based medicine; HF = heart failure; PNE = pneumonia; SIP = surgical care improvement and infection prevention; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
[a]*N* varies from 936 to 1,004 observations.
[b]*N* = 1,014 except where noted.

support functionality and EMAR. This is a key control because a broader scope of automation would create increased incentives for the hospital to push for increased CPOE usage. Finally, the vendor of the CPOE system is taken from the HIMSS Analytics Database. The vendor is used as an instrumental variable.

Table 2. CPOE Usage.

Use (%)	Hospitals	%
0	355	35
1–25	216	21
26–50	81	8
51–90	116	11
91–100	246	24

Note. CPOE = computerized physician order entry.

Selection Correction

Empirical specification to assess IT usage impacts will need to account for potential endogeneity of usage with dependent variables. Hospitals that are more likely to encourage or enforce the use of the electronic system probably have greater expectations for returns in terms of salary cost reductions and compliance (Restuccia et al. 2012). Therefore, we use a selection correction approach that relies on the use of appropriate instrumental variables.

Selection correction requires the use of instrumental variables. Two suitable instruments were present in our data sets. The first instrumental variable, CPOE system vendor, is useful when instrumenting for both cost and process compliance. The rationale behind this instrumental variable is that different systems will be more or less easy to use (Radley et al. 2013). As ease of use is largely determined by the vendor's approach to the user interface, systems from one vendor may be more likely to be used than systems from another vendor. Vendor impact on performance outcomes will therefore be primarily realized through user experience and extent of usage. For all hospitals that reported a specific vendor, dummy variables were generated to represent the top four vendors of CPOE systems (accounting for more than 60 percent of the CPOE market share). A number of hospitals responded that their system was "self-developed." This category could be potentially different in terms of CPOE usage; therefore, we created a separate dummy variable for these hospitals. The final category represented all other hospitals that stated their vendor. We grouped together the hospitals that report CPOE adoption but no vendor and designated the set as the comparison group.

The second instrumental variable, physicians employed by the hospital, is useful when instrumenting for pharmacy and nursing salary costs but not for process compliance. This variable captures the relationship between physicians and the hospital. There are an increasing number of hospitals employing physicians as intensivists, hospitalists, and in other positions within the hospital. This is in contrast to the traditional model where physicians are not employed by the hospital. When the hospital employs the physician, we expect that the hospital will have more ability to encourage physicians to use the CPOE system. Because hospitals with more employed physicians will have an advantage in enforcing policy compliance, this variable is not used as an instrument when compliance is the dependent variable. Nevertheless, it is used as a control variable. We expect that the number of physicians employed by the hospital will be a better instrument in the models related to salary. The number of full-time equivalent (FTE) physicians was divided by patient days to standardize the measure across hospitals that saw different numbers of patients.

We use a variant of the original selection correction model developed in Heckman (1979). Whereas the original selection model addresses situations where a probit model is required in the first stage (or selection equation), the model used in this study is an adaptation suited to an *ordered probit* model in the selection equation (Chiburis and Lokshin 2007). We have chosen an ordered probit selection model because (1) selection bias is likely present in the data and (2) the first stage must predict the ordered CPOE usage category. This model has been implemented in the OHECKMAN procedure in Stata 11.

Because usage is determined in part by the benefits that can be derived from usage, an estimation of equation (1) yields inconsistent results:

$$y = c + \beta x + \delta w + \varepsilon, \tag{1}$$

where y = quality or cost, x = exogenous variables such as controls and IT factors, and w = the endogenous discrete ordered usage category variable.

The first stage of the Heckman selection correction estimates the probability of selection into each level of usage. Independent variables in this stage will include factors related to the adoption of relevant EHR technology, organizational structure, as well as vendor dummies. The first stage of the ordered probit is estimated as follows:

$$w = c + \gamma z + \pi x + \varepsilon, \tag{2}$$

where z is a selection restriction variable.

Similar to a two-stage residual inclusion (2SRI) model (Terza, Basu, and Rathouz 2008), an inverse Mill's ratio $(\hat{\lambda})$ is calculated from the first stage (equation (2)). The second stage uses $(\hat{\lambda})$ to correct for endogeneity and consistently estimate an equation for each discrete value contained in w. After obtaining consistent estimates for β, it is possible to estimate the unbiased γ. The final step is to estimate the unbiased outcome variable across different levels of usage. Coefficients were estimated using a two-step estimator because they are more robust against non-normal shocks (Chiburis and Lokshin 2007).

Results

Selection Restrictions and Selection Equation

Before finalizing the empirical specification, we assessed instrument validity using the Wald test. Estimates were bootstrapped with one hundred replications for each analysis. The Wald tests showed mixed results. CPOE vendor and the number of FTE physicians was a valid instrument for pharmacy salaries and nursing salaries ($p < .05$). CPOE vendor was a valid instrument for heart attack and surgical care improvement and infection prevention ($p < .05$). The instruments were not suitable for process compliance related to HF and PNE. As such, we compared the two-stage results for HF and PNE with the results from single-stage analysis. The single-stage analysis estimates were qualitatively similar to the original model. For simplicity, we report the Heckman selection correction model for all variables.

Table 3 presents the selection regression that forms the basis for all second-stage analyses. The

Table 3. Ordered Probit Selection Equation—Dependent Variable = Percent Orders Entered Electronically.

Dependent variable = CPOE usage	
CPOE Vendor 1	−0.158
CPOE Vendor 2	0.023
CPOE Vendor 3	0.588***
CPOE Vendor 4	0.157
CPOE Self-Developed	−0.252
CPOE Vendor Other	0.003
Employed Physicians	0.287***
CPOE Decision Support	0.401***
EMAR	0.214***
Ln(bed size)	0.013
Medicare payer mix	−0.008**
Medicaid payer mix	0.000
Sophistication index	−0.007
Government run	0.031
For-profit run	−0.267**
Member of a system	0.315***
JCAHO accreditation	−0.325**
Rural location	0.135
COTH member	0.372***
Medical school affiliation	0.080
Region_se	−0.113
Region_sc	−0.021
Region_nc	−0.116
Region_mt	−0.211
Region_pa	0.100

Note. CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission. *Significant at .10. **Significant at .05. ***Significant at .01.

instrumental variables showed significant association with CPOE usage. The number of employed physicians per patient day was strongly associated with higher CPOE systems usage. One CPOE vendor stood out as strongly associated with usage (vendor names are masked to honor data use agreements). Vendor 3 showed significantly higher CPOE usage against the control group of hospitals that did not identify their vendor in the data set. Interestingly, self-developed CPOE systems were not significantly associated with higher CPOE usage level. Because of the structure of these dummy variables, using the coefficients to evaluate vendor performance would not be appropriate. Nevertheless, the dummies have provided a useful instrumental variable.

The first-stage regression also showed that decision support system automation and EMAR were strongly associated with CPOE usage. The results support our initial assumption that extent of EHR adoption in medication management process affects CPOE usage level. There is minimal difference in use by geographic region after controlling for other factors.

Several other relevant controls were related to usage of CPOE systems. Hospitals with a higher Medicare payer mix were associated with lower levels of usage. However, Medicaid patient mix showed no significant effect. For-profit hospitals used CPOE for a smaller percent of orders than do not-for-profit hospitals. Not surprisingly, hospitals that are part of a system used their systems more than independent hospitals. Members of the Council of Teaching Hospitals (COTH) reported more use of their systems while those who were accredited by the Joint Commission were associated with less use.

CPOE Usage and Salary Costs

Second-stage selection corrected regressions were run for each usage category (see the Technical Appendix). The second-stage regressions were then used to estimate unbiased costs given specific levels of usage (see Figure 1). Further details regarding second-stage regressions, including the effect of the control variables on cost and compliance by usage group, are available from the authors upon request. Within different usage levels, the second-stage regressions showed that the IT variables were generally not significantly associated with the salary costs. These findings support the assumption that system usage mediates the association of EHR technologies with process costs. Although this may seem obvious, most research related to EHR technologies have only been able to observe adoption and not usage. The results in this paper demonstrate the importance of measuring usage.

To test the association of CPOE usage levels with salary costs, we performed pairwise two-tailed t-tests. The t-test scores did not support statistically significant differences in salary costs between sequential usage levels from no usage up to 50 percent usage (ps = .472, .310). Predicted

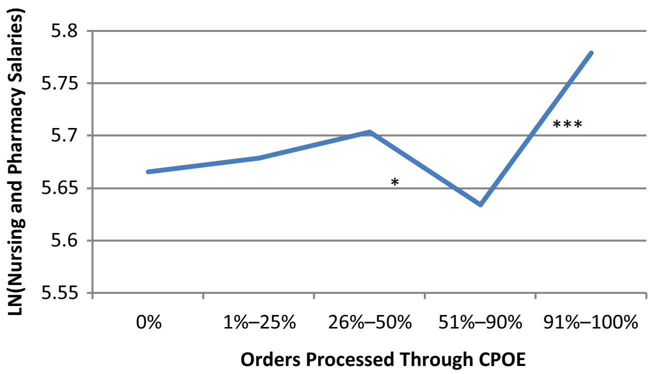

Figure 1. Predicted pharmacy and nursing salaries at different levels of CPOE use.
Note. CPOE = computerized physician order entry.
For *t*-test performed between adjacent points: *Significant at .10. **Significant at .05. ***Significant at .01.

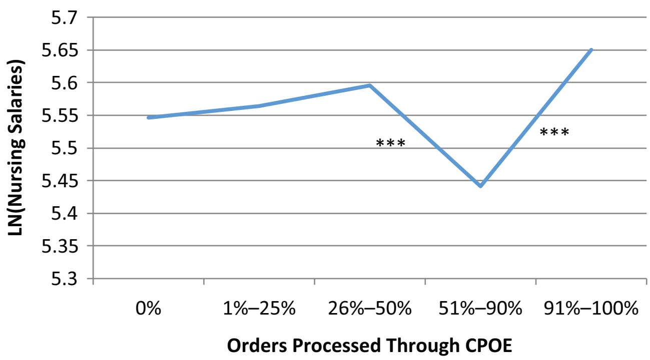

Figure 2. Predicted nursing salaries at different levels of CPOE use.
Note. CPOE = computerized physician order entry.
For *t*-test performed between adjacent points: *Significant at .10. **Significant at .05. ***Significant at .01.

salary costs dropped at 51 to 90 percent usage (marginally significant, p = .086) and then climbed sharply at the highest usage level ($p <$ .001). We therefore conclude that salary costs are associated with usage in a non-linear manner. However, the hypothesis that CPOE usage is associated with higher levels of efficiency did not hold for all usage levels.

We separately analyzed the nursing and pharmacy salary costs to examine if CPOE usage has differential impacts on the two cost centers. Figures 2 and 3 show the predicted nursing salary and pharmacy salary costs per patient day. As seen in Figure 2, nursing salary costs mimic the pattern in Figure 1. Nursing salary costs do not show a significant change between no system usage to 50 percent usage (ps = .297, .208). There was a significant drop in and then rise in nursing salary costs per patient day at the higher usage levels (ps = .003 and <.001, respectively).

In contrast to nursing salary costs, pharmacy salary costs exhibited a different pattern with respect to usage levels (see Figure 3). From 0 to 50 percent usage, there was no statistical difference in pharmacy salary costs (ps = .425, .369). Predicted pharmacy salary cost rose at 51 to 90 percent usage (p = .007). However, costs at the highest level of usage were not significantly different from that at 51 to 90 percent (p = .619). A two-tailed t-test comparing the final

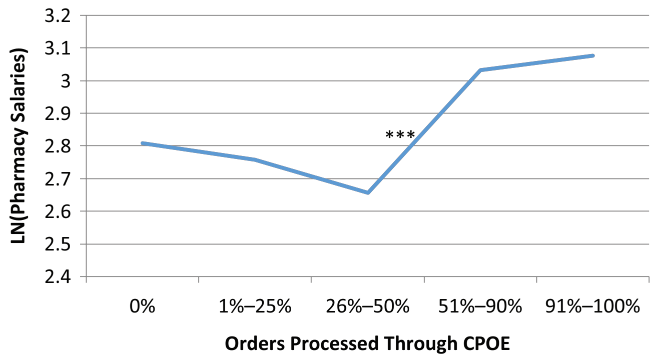

Figure 3. Predicted pharmacy salaries at different levels of CPOE use.
Note. CPOE = computerized physician order entry.
For *t*-test performed between adjacent points: *Significant at .10. **Significant at .05. ***Significant at .01.

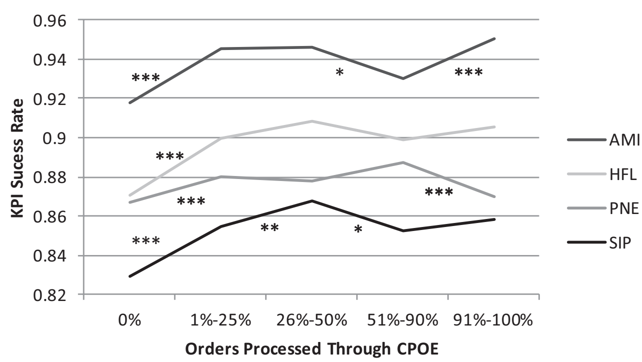

Figure 4. Predicted quality at different levels of CPOE use.
Note. CPOE = computerized physician order entry; KPI = key performance indicator; AMI = acute myocardial infarction; HFL = heart failure; PNE = pneumonia; SIP = surgical care improvement and infection prevention.
For *t*-test performed between adjacent points: *Significant at .10.
**Significant at .05. ***Significant at .01.

level (91–100 percent usage) to the first three (0–50 percent usage) levels was statistically significant ($p < .001$).

CPOE Usage and Process Compliance

We found partial support for the hypothesis that CPOE usage is associated with increased process compliance (see Figure 4). The *t*-tests in predicted quality levels showed that a significant improvement in quality existed between no usage and 1 to 25 percent usage in all cases (all $ps < .01$). Results were mixed above 25 percent usage but mostly flat. Because the instrumental variables were weak in relation to PNE and HF, we also ran the similar tests of significance after a single-stage model. These results were qualitatively similar to the ones shown in the Figures with the exception that changes in compliance related to PNE were less significant. Second-stage selection-corrected regressions are available in the Technical Appendix.

Discussion

Expectations of improvements in process efficiency and quality are a major driver for promoting CPOE usage in the medication management process. Despite the recent push to incentivize EHR and other technology usage in clinical processes, there is scant empirical evidence for whether usage improves quality and efficiency. Our findings based on available CPOE usage information from U.S. hospitals show a non-linear association of CPOE usage with salary costs and process compliance. We find support for the hypothesis that CPOE usage is associated with increased process compliance. However, we do not find support for the hypothesis that CPOE usage is associated with lower labor costs. The complex non-linear relationship seen in our results emphasizes the need to consider usage impacts in policy decisions. We find that the extent of related automation, CPOE vendors, and the number of employed physicians are associated with usage. We find little support for the direct effect of CPOE adoption on cost and quality (see the Technical Appendix); the effects come largely through CPOE usage. The empirical results provide interesting insights for hospital administrators on the implications of increasing CPOE usage in the medication management process. The findings are also directly relevant to debate surrounding the efficacy of the MU rule of the HITECH act.

Process Costs

We find that CPOE usage in hospitals can yield benefits even when 100 percent usage is not attained. In relation to nursing costs per patient day, 51 to 90 percent usage is associated with the lowest predicted costs. A large increase in nursing salaries is associated with 91 to 100 percent usage. For the pharmacy, the most beneficial cost outcomes accrue at under 50 percent usage. While noting that pharmacy and nursing salary costs are not the only costs associated with use of the CPOE system, we conclude that it might actually be possible to achieve the beneficial impacts of CPOE systems even when 100 percent CPOE usage is not attained. It appears from the results that forcing all orders through the system can especially impact nursing salary costs.

The cost curves associated with usage suggest that roles in the hospital may be changing with the adoption of EHR systems. As a follow-up to the analysis, we conducted informal interviews with pharmacy and clinical IT managers at three different hospitals. Pharmacy managers, especially in the larger hospitals, pointed out that their pharmacists were now taking on different roles. Pharmacists now approve medications from any location in the hospital and were much more likely to consult with physicians and patients face-to-face. They also spent more time educating patients. This change in roles is clearly a possible explanation that pharmacy costs rise with usage of CPOE (Rough and Melroy 2009).

A pharmacy manager at a smaller hospital provided an example that could explain why pharmacy costs were unevenly associated with usage. When CPOE adoption was implemented at the hospital, pharmacists were running a pneumatic system, the fax machine, as well as a CPOE system that did not integrate with a pharmacy system. At the time of the interview, orders were arriving through all three sources. Managing and reconciling these sources of orders and the processes for each required substantial resources. Running multiple processes is a plausible explanation for a spike in costs in the 51 to 90 percent usage level.

The pattern in predicted nursing salary cost was equally puzzling. In traditional (non-electronic) systems, nurses or nursing staff have been responsible to enter changes to orders. This requires time in recording and calling back doctors to verify illegible or unusual orders. Under some circumstances, nurses were required to validate orders. The nurses coordinated with the pharmacy to communicate orders. It is conceivable that when 51 to 90 percent of orders are going through CPOE, the nursing staff is relieved of some of these responsibilities. Furthermore, at this point, all the physicians who can or will use the system without help are doing so.

We find that nursing labor costs rise significantly at the highest level of usage. Consistent with the prediction of the theory of innovation diffusion (Bass 1969; Rogers 1962), non-linearity in usage impact may be associated with the different costs of bringing physicians onboard with the CPOE. Among possible explanations is that the final group of physicians to adopt CPOE will need significant coaching and are possibly resistant to use (Fichman and Kemerer 1999). Hospitals may be expending resources (in additional nurse and administrative support) to get buy-in from physicians who are not part of the hospital pay structure. The hospital may need to provide this kind of on-site, just-in-time support because physicians may be reluctant to invest time in training. Our interviewees indicated this was a fairly common occurrence in community hospital settings. More work is needed in understanding the underlying reasons for the non-linearity in nursing and pharmacy labor cost curves.

Process Quality Outcomes

From a quality perspective, 100 percent CPOE usage is also not essential to realizing beneficial outcomes. Compliance with process standards increased substantially between the 0 percent usage level and the first level of usage for all four process quality measures. The patterns in the compliance curves suggest diminishing marginal returns to CPOE usage. It may be possible that either the tasks associated with the orders that are last to be automated or the orders themselves are not well suited to the electronic systems as currently implemented. The downward trend at higher levels of usage is unexpected and potentially dangerous. An alternative explanation is that when systems are used to record more data, it is possible to discover issues related to compliance that were not visible until digital documentation was completed. Further research should confirm and explore this negative trend at high levels of usage.

The quality curve shows the most improvement with minimal usage. Our findings reflect previous work (e.g., Encinosa and Bae 2011) in that hospitals with any level of usage have higher quality than hospitals that do not use electronic order entry. However, our findings suggest that the benefits come in the first stages of CPOE usage. It could also be that physicians become aware of ordering suggestions, policies, and newly discovered drug interactions by using the system part of the time. However, discussions with pharmacy and hospital representatives suggest that CPOE is not generally implemented across the hospital in small increments, but rather by departments, making the learning hypothesis less likely. It may be that hospitals that implement CPOE first implement it in departments or areas of the hospital that are most prone to errors. When this is the case, the largest return on investment from the use of CPOE is in these trouble areas. Further use of CPOE may have only marginal returns on quality. In addition, hospitals that have chosen to implement a CPOE system may have other quality initiatives in place (Restuccia et al. 2012).

Limitations and Future Research

Several questions and limitations need to be addressed. The sample in this study is limited to hospitals that have already adopted CPOE. The study covers only one year of CPOE usage. As data become available, longitudinal analysis may enable researchers to examine the effects of experience and learning on outcomes. We also note that data for this study predate the implementation of HITECH investments by the federal government. As usage increases, the effects of usage will become more apparent. Time will also change the systems that are being studied. As CPOE interfaces improve, we may see more compliance with EBM-related policies. The measure of CPOE usage used in this study is self-reported and potentially affected by a reporting bias. Future work should seek more objective measures of usage when available.

Furthermore, this work only observes CPOE usage; the literature and findings suggest that all points of IT usage in the process may be of interest. There may be additional dimensions of CPOE usage that impact outcomes in different ways. Selection bias in the context of CPOE usage is still a significant challenge. The instruments used in this study proved suitable for the context of four of six dependent variables. Future research should seek more instrumental variables to better understand selection bias in this context.

Implications and Key Findings

From the academic research perspective, a key finding of this study is that CPOE usage is a critical determinant in predicting process outcomes. Due to the lack of usage data, most academic research focuses on adoption and assumes usage. Given the cost and quality curves seen in this analysis, it is reasonable to suggest that much of the mixed findings with CPOE adoption in the literature come from the omission of system usage in research models. Furthermore, the analysis suggests that accounting for all of the EHR technologies in the process is important for accurate estimation of the effects of CPOE and CPOE usage on outcome variables. The results also demonstrate that IT and organizational factors affect usage. Usage in turn affects performance; it is therefore vital to account for usage where possible. Another critical finding revealed by the analysis is the need to correct for endogeneity. Endogeneity in IT adoption has traditionally been a difficult problem to solve though it has been recognized regularly as a potential issue (Encinosa and Bae 2011; Furukawa, Raghu, and Shao 2010a). Where possible, future research on the effects of IT usage must account for endogeneity.

One implication of our findings relates to the optimization of CPOE and other EHR technologies. After EHR technologies have been implemented, substantial long-term efforts must be made to optimize the system to hospital processes and where necessary, change processes to be more efficient in the digital environment (e.g., Smith 2012). The cost and compliance curves seen in the results suggest that hospitals must optimize systems before striving to reach 100 percent usage. As hospital processes continue to develop and users become more comfortable with technology infusion, more benefits may accrue through higher levels of usage. Optimization efforts focused on customizing workflows and care sets for each specialty hold considerable promise. Systems may also need to be optimized through personalization capabilities at the individual clinician level.

Another implication of our findings is that administrators must evaluate the effect of new systems on all stakeholders in the process as well as the individual tasks that are completed using the system. Furthermore, decision makers must recognize that automation of the medication management process does not always reduce costs. This analysis supports the conclusion that labor costs generally rise with the extent of automation. One finding of interest to both researchers and practitioners is seen when considering both quality and labor costs simultaneously. Because costs seem to rise with 100 percent use of CPOE and the largest jumps in quality happen in the 1 to 25 percent usage category, hospitals may accrue benefits from CPOE much earlier than anticipated.

Finally, this study has direct implications for policy makers. Because adoption of EHR systems has been slow (Furukawa et al. 2008), regulators have placed incentives on the implementation and use of EHR systems through the Medicare and Medicaid programs. The third and final stage is expected to move the bar up in terms of use of clinical systems. The analysis here should serve as a caution to policy makers not to push the use of clinical systems too far too quickly. If other systems face cost and compliance curves similar to CPOE, doing so could lead to spikes in labor cost and potential decreases in quality.

The findings of this study provide hope that many of the benefits of CPOE can be obtained in hospitals before 100 percent usage is achieved. This recognition is important because concerns about fit with other EHR technologies and ease of use have hindered the adoption and use of CPOE within the hospital (Holden 2010; Wachter 2006). Furthermore, it may be unwise to push all hospitals to 100 percent usage if the nature and fit of CPOE systems within the medication management process do not change.

Conclusion

The MU provision of the HITECH Act of 2009 provides incentives for hospitals to increase CPOE usage in the medication management process. The policy impetus is based on the assertion that CPOE usage improves process quality and efficiency. However, there is not yet empirical evidence of CPOE usage improving either process quality or efficiency. In this research, we set out to assess CPOE usage impacts on efficiency and process compliance related to medication management in acute-care hospitals. Our findings suggest a non-linear relationship between CPOE usage and process outcomes.

Our findings suggest that CPOE benefits may accrue well before the attainment of 100 percent usage. Recognition of this fact is important in the current policy and legislative landscape, given that not all hospitals may be able to quickly attain high usage levels due to endogenous organizational factors. Unlike past studies that relied primarily on adoption data, we show that usage is a critical factor in understanding CPOE impacts of process outcomes. Until the merging of these data sets, this detail has been difficult to observe in the health care industry. Actual IT usage provides a better lens through which to judge the impact of automation on the medication management process. The non-linear relationship between usage and process outcomes suggests the need for hospitals to focus on optimization after adoption as a viable future strategy to improve efficacy of care delivery in the medication management process. Optimization efforts would ideally focus on both workflow improvements at the unit level and personalization of system features at the user level.

Technical Appendix

Details of the Second-Stage Regressions Including Heckman Correction

Although the second-stage regressions are not sufficient to test the hypotheses, they provide some evidence to evaluate the impact of adoption on salary costs and process quality after factoring out computerized physician order entry (CPOE) usage. Coefficients presented in Tables A1, A2, and A3 should be interpreted as the regressors' effect among hospitals with the given level of CPOE usage. Note that the IT coefficients (decision support and Electronic Medication Administration Records [EMAR]) are largely insignificant. This suggests that adoption (without usage) has almost no impact on pharmacy salary costs, nursing salary costs, or compliance.

Table A1. Regression on Ln(Pharmacy and Nursing Salaries per Patient Day) Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	−0.068	0.010	0.206	−0.145	−0.212**
CPOE decision support	−0.031	−0.020	0.257**	−0.117	−0.022
EMAR	0.065*	0.016	0.041	0.118	−0.002
Ln(bed size)	−0.111***	−0.096***	−0.005	−0.026	−0.105***
Medicare payer mix	−0.002	−0.002	−0.008**	0.007*	−0.003
Medicaid payer mix	−0.006***	−0.008***	−0.004	−0.004	−0.003*
Sophistication index	0.022**	0.025*	0.006	−0.034	−0.015
Government run	0.027	0.045	0.150	0.142	0.029
For-profit run	−0.033	−0.111	−0.169	0.124	−0.167**
Member of a system	−0.044	0.021	0.042	−0.071	−0.082*
JCAHO accreditation	0.091	0.091	−0.059	−0.022	−0.208***
Rural location	0.020	0.068	0.105	0.007	−0.365***
COTH member	0.028	0.102	−0.004	−0.011	0.136**
Medical school affiliation	−0.008	−0.039	0.058	0.235*	−0.006
Region_se	−0.201***	−0.167***	−0.050	0.266*	0.036
Region_sc	−0.324***	−0.313***	−0.214*	0.044	−0.215***
Region_nc	0.043	−0.032	0.166	0.466***	0.027
Region_mt	0.004	−0.066	−0.041	0.464**	0.105
Region_pa	0.371***	0.073	0.413***	0.784***	0.365***
Constant	6.259***	6.319***	5.950***	5.452***	7.063***

Note. CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
*Significant at .10. **Significant at .05. ***Significant at .01.

Table A2. Regression on Ln(Nursing Salaries per Patient Day) Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	−0.114	0.091	0.145	0.063	−0.242**
CPOE decision support	−0.043	0.007	0.233*	−0.076	−0.042
EMAR	0.048	0.050	0.012	0.134	−0.006
Ln(bed size)	−0.109***	−0.089***	−0.022	−0.043	−0.117***
Medicare payer mix	−0.001	−0.003	−0.009*	0.009	−0.003
Medicaid payer mix	−0.005***	−0.008***	−0.003	−0.003	−0.004**
Sophistication index	0.017*	0.024*	0.010	−0.042	−0.016
Government run	0.021	0.055	0.112	0.218	0.055
For-profit run	−0.022	−0.135*	−0.235	0.052	−0.154**
Member of a system	−0.077*	0.057	0.063	0.014	−0.069
JCAHO accreditation	0.088	0.011	−0.115	−0.087	−0.193**
Rural location	0.016	0.113	0.130	0.040	−0.290***
COTH member	0.000	0.092	−0.082	−0.120	0.118*
Medical school affiliation	0.003	−0.036	0.081	0.414*	−0.004
Region_se	−0.183***	−0.177***	−0.021	0.401	0.040
Region_sc	−0.280***	−0.327***	−0.163	0.200	−0.211***
Region_nc	0.078	−0.059	0.190*	0.665***	0.015
Region_mt	0.005	−0.156*	−0.110	0.636*	0.065
Region_pa	0.369***	0.077	0.390***	1.014***	0.319***
Constant	6.046***	6.262***	5.967***	4.966***	7.065***

Note. CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals.
*Significant at .10. **Significant at .05. ***Significant at .01.

Table A3. Regression on Ln(Pharmacy Salaries per Patient Day) Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	0.563	−1.195*	2.243**	0.003	0.125
CPOE decision support	0.030	−0.400	1.278**	−0.097	0.203
EMAR	0.199	−0.636**	0.637	0.333	0.055
Ln(bed size)	−0.025	−0.006	0.339	0.856***	0.059
Medicare payer mix	−0.021**	0.020	−0.008	0.021*	0.015
Medicaid payer mix	−0.009	−0.011	0.016	0.018	0.017*
Sophistication index	0.126**	0.054	−0.035	−0.129	0.012
Government run	0.049	−0.310	0.738	−0.104	−0.500*
For-profit run	−0.099	0.503	0.341	0.533	−0.469
Member of a system	0.424*	−0.539	0.371	−0.139	−0.398*
JCAHO accreditation	0.193	1.474***	0.759	0.146	0.061
Rural location	−0.285	−0.846	−0.626	−0.447	−1.753***
COTH member	0.120	0.336	1.103	0.582	0.374
Medical school affiliation	−0.311	−0.263	−0.365	−0.580	−0.133
Region_se	−0.882***	−0.358	−0.618	0.199	−0.233
Region_sc	−1.478***	−0.597	−1.178**	0.114	−0.706**
Region_nc	−0.935***	−0.084	−0.338	−0.229	−0.499*
Region_mt	−0.730*	0.863	−0.259	0.038	−0.068
Region_pa	0.186	−0.254	0.979	0.223	0.898**
Constant	4.538***	1.309	−0.365	−1.807	2.159*

Note. CPOE = computerized provider order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
*Significant at .10. **Significant at .05. ***Significant at .01.

Table A4. Regression on Compliance Processes Related to Heart Attack (AMI) Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	0.019	0.065**	−0.008	−0.012	−0.013
CPOE decision support	0.010	0.039**	0.039	−0.022	0.002
EMAR	0.000	0.028*	0.030	0.020	0.002
Ln(bed size)	0.023**	0.022*	−0.001	−0.002	−0.002
Medicare payer mix	0.020**	0.009	0.033***	0.001	0.011
Medicaid payer mix	0.000	0.000	−0.001	−0.002	0.000
Sophistication index	−0.001*	0.000	−0.002*	−0.001	0.000
Government run	0.006**	0.005	0.011*	0.009	0.004
For-profit run	−0.030**	−0.036**	0.024	−0.068*	−0.015
Member of a system	0.018	−0.028	0.039	−0.062	−0.015
JCAHO accreditation	0.015	0.035**	0.031	−0.012	0.018**
Rural location	0.025	0.009	−0.008	0.062	0.020
COTH member	−0.027	−0.059**	0.040	0.020	−0.034
Medical school affiliation	0.012	0.019	−0.047*	−0.025	−0.011
Region_se	0.005	0.018	−0.008	−0.007	−0.006
Region_sc	−0.023	−0.038**	0.010	−0.008	−0.006
Region_nc	−0.037**	−0.033*	−0.058**	−0.055*	−0.025**
Region_mt	0.003	−0.024	−0.018	0.000	−0.011
Region_pa	−0.018	−0.017	0.000***	−0.042	0.008
Constant	−0.019	0.007	0.023	0.002	0.004

Note. AMI = acute myocardial infarction; CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
*Significant at .10. **Significant at .05. ***Significant at .01.

Table A5. Regression on Compliance Processes Related to HFL Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	−0.006	0.054	−0.016	0.009	0.006
CPOE decision support	0.007	0.056**	−0.023	−0.012	0.002
EMAR	−0.013	0.034*	−0.001	0.002	0.006
Ln(bed size)	0.007	0.025	0.047**	−0.050**	0.016
Medicare payer mix	0.018	0.017	0.003	−0.017	−0.007
Medicaid payer mix	0.000	0.000	−0.001	−0.002	−0.001
Sophistication index	−0.001	0.000	−0.002*	−0.001	−0.001
Government run	0.003	0.001	0.016*	0.010*	0.002
For-profit run	0.014	0.004	0.044	−0.040	0.016
Member of a system	0.005	−0.034	−0.007	−0.062	−0.005
JCAHO accreditation	0.025	0.054**	0.007	0.036	0.028**
Rural location	−0.004	0.027	−0.104**	0.074*	−0.020
COTH member	−0.035	−0.001	−0.033	0.001	−0.044
Medical school affiliation	0.023	0.012	−0.008	−0.038	0.007
Region_se	0.012	0.012	−0.002	0.000	0.006
Region_sc	0.025	−0.042*	−0.014	−0.056*	0.032*
Region_nc	−0.006	−0.010	−0.034	−0.019	0.000
Region_mt	0.021	−0.021	0.022	−0.007	0.014
Region_pa	0.004	−0.030	0.107	0.007	0.039
Constant	0.028	0.014	0.035	−0.013	−0.004

Note. HFL = heart failure; CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
*Significant at .10. **Significant at .05. ***Significant at .01.

Table A6. Regression on Compliance Processes Related to PNE Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	−0.040	0.018	0.065	0.077*	−0.004
CPOE decision support	−0.009	−0.008	0.025	−0.016	−0.008
EMAR	−0.012	0.009	0.047*	0.028	0.006
Ln(bed size)	0.008	0.033**	0.038*	0.009	0.025**
Medicare payer mix	0.012	0.002	0.010	−0.002	0.000
Medicaid payer mix	0.001	0.000	−0.001	0.000	−0.001
Sophistication index	−0.001	0.000	0.000	0.001	−0.001*
Government run	0.007**	0.006	0.015**	0.003	0.006*
For-profit run	−0.017	−0.012	0.034	−0.009	−0.050***
Member of a system	0.015	−0.007	−0.098**	−0.085***	−0.028
JCAHO accreditation	0.021	0.025	0.090***	0.045**	0.012
Rural location	0.029	0.032	−0.068*	0.009	0.029
COTH member	−0.007	−0.006	0.002	−0.019	−0.021
Medical school affiliation	−0.072***	−0.027	−0.021	−0.023	−0.037**
Region_se	−0.013	−0.001	0.037*	0.005	−0.033***
Region_sc	−0.034**	−0.040**	−0.038	−0.074***	−0.014
Region_nc	−0.039**	−0.032*	−0.015	−0.020	−0.007
Region_mt	0.002	0.003	0.012	−0.016	−0.009
Region_pa	−0.054**	−0.026	0.222**	−0.042	−0.010
Constant	−0.041**	−0.031	−0.027	−0.025	−0.006

Note. PNE = pneumonia; CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
*Significant at .10. **Significant at .05. ***Significant at .01.

Table A7. Regression on Compliance Processes Related to SIP Using Heckman Selection Correction Selection Equation.

Usage	0%	1–25%	26–50%	51–90%	91–100%
Inverse Mills	−0.010	0.053	0.153**	0.070	0.006
CPOE decision support	−0.006	0.035	0.060	0.036	0.006
EMAR	0.002	0.030	0.089**	0.040	0.000
Ln(bed size)	−0.001	0.041**	0.011	0.007	0.004
Medicare payer mix	0.011	−0.001	0.011	−0.004	0.019*
Medicaid payer mix	−0.001	−0.001	−0.002	−0.001	0.000
Sophistication index	−0.001**	−0.001	0.001	−0.002	0.000
Government run	0.001	0.003	0.017*	0.003	0.002
For-profit run	−0.034*	−0.040*	0.004	−0.077*	−0.032*
Member of a system	0.003	−0.030	−0.151***	−0.064	−0.051**
JCAHO accreditation	0.032	0.037*	0.079**	0.070**	0.021
Rural location	0.026	−0.040	−0.051	0.018	0.003
COTH member	−0.028	−0.095**	0.082	−0.014	−0.029
Medical school affiliation	−0.024	0.027	0.001	0.025	−0.013
Region_se	−0.012	0.000	0.026	0.020	−0.007
Region_sc	−0.025	−0.035	0.008	−0.020	−0.027
Region_nc	−0.096***	−0.052**	−0.001	−0.030	−0.050**
Region_mt	−0.012	−0.048**	0.037	−0.002	−0.009
Region_pa	−0.071**	−.072**	0.229**	−0.080	−0.042
Constant	−0.098***	−0.043	−0.001	−0.057	−0.065***

Note. SIP = surgical care improvement and infection prevention; CPOE = computerized physician order entry; EMAR = electronic medication administration records; COTH = Council of Teaching Hospitals; JCAHO = Joint Commission.
*Significant at .10. **Significant at .05. ***Significant at .01.

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