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ABSTRACT **Health information technology (IT), such as computerized physician order entry and electronic health records, has potential to improve the quality of health care. But the returns from widespread adoption of such technologies remain uncertain. We measured changes in the quality of care following adoption of electronic health records among a national sample of U.S. hospitals from 2004 to 2007. The use of computerized physician order entry and electronic health records resulted in significant improvements in two quality measures, with larger effects in academic than nonacademic hospitals. We conclude that achieving substantive benefits from national implementation of health IT may be a lengthy process. Policies to improve health IT's efficacy in nonacademic hospitals might be more beneficial than adoption subsidies.**

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Clinical errors cause at least 44,000 deaths annually in the United States. These deaths largely result from process errors, or the failure to provide recommended treatments for patients with certain medical conditions. With direct medical costs estimated at $17 billion annually, these errors impose a substantial burden on both the health care system and society as a whole.[1,2]

Health information technology (IT) systems such as electronic health records and computerized physician order entry hold the potential to improve quality while reducing costs. In particular, they are designed to improve communication among the disparate providers within a health care organization. Furthermore, these technologies facilitate the implementation of care guidelines and decision-support tools, which may be particularly valuable in preventing process errors.

The Institute of Medicine[1,3] has advocated adoption of computerized physician order entry to reduce inpatient errors. Furthermore, the American Recovery and Reinvestment Act (ARRA) of 2009 established financial incentives for hospitals to become meaningful users of health IT. We measured changes in six process-quality measures following adoption of both electronic health records and computerized physician order entry from 2004 to 2007, and we found that adoption resulted in significant improvements in two of the measures. These effects were larger in academic hospitals.

Past studies of health IT's impact have shown mixed results. Richard Hillestad and colleagues estimated that clinical IT may yield savings of up to $142 billion annually.[4] Numerous studies provide evidence that health IT may improve clinical quality, partly through the reduction of errors after its adoption.[5–7]

These studies provide crucial insight into the function and value of health IT. Although the results are encouraging, they are almost entirely based on single-hospital studies within large academic medical centers. Furthermore, implementation and design problems, such as inefficient interfaces or incomplete data records, may decrease the societal value of health IT.[8–10] Some studies have found empirical evidence that health IT may even reduce clinical quality through work-flow disruption or poor interface design.[11] It remains to be seen whether substantive returns from the adoption of health IT can be experienced by a wide range of U.S. hospitals.

More recently, cross-hospital studies have suggested that the returns stemming from health IT may be broad-based. Ruben Amarasingham and colleagues[12] studied the relationship between the level of automation and such outcomes as inpatient mortality, complications, and length-of-stay in forty-one Texas hospitals in 2005 and 2006. They found evidence that quality was higher in hospitals with more health IT.

Similarly, Feliciano B. Yu and colleagues[13] examined the relationship between computerized physician order entry and process-quality measures for 3,364 hospitals using 2004 data. They found that hospitals that had fully implemented computerized physician order entry outperformed other hospitals in five of eleven medication-related measures and in one of nine other measures.

Conversely, David Himmelstein and colleagues[14] studied the effect of computerization on quality in 3,310 hospitals, using process measures for acute myocardial infarction, heart failure, and pneumonia from 2001–2005. They found that computerization made little difference in quality.

Stephen Parente and Jeffrey McCullough[15] took a different approach and examined the change in quality in individual hospitals following adoption of electronic health records. They examined a national sample of 2,707 hospitals during 1999–2002 and found that use of these records was associated with small but significant reductions in infections attributable to medical care. They also found evidence of selection bias in health IT adoption. Specifically, adopting and nonadopting hospitals systematically differ in quality for reasons not readily explained by secondary data. This implies that cross-hospital studies that do not look across time will produce biased estimates of the value of health IT.

We build on this literature by measuring the effect of computerized physician order entry and electronic health records on quality. Furthermore, we allow for the returns from health IT adoption to vary across different types of hospitals—specifically, academic and nonacademic institutions.

We employ a novel data set that describes hospitals' health IT adoption decisions and other hospital characteristics. The health IT data are combined with data on hospital process-quality measures. The process-quality metrics capture the rate at which hospitals provide recommended treatments for patients with certain medical conditions, rather than the frequency of quality outcomes.

Although both types of measures are interesting, process quality is more directly controlled by hospital decisions than is the frequency of quality outcomes. Our data follow hospitals across time, allowing us to study the changes in particular quality measures that followed the adoption of health IT within individual hospitals. We also studied potential heterogeneity in the returns from health IT investments in different settings.

Study Data And Methods

DATA Our sample comprises 3,401 nonfederal, acute care U.S. hospitals and spans 2004–2007. Data are drawn from three sources.

The American Hospital Association's (AHA's) annual survey describes hospital characteristics that are used as control variables and is a near-census of U.S. hospitals. The Health Information and Management Systems Society (HIMSS) Analytics database describes hospitals' health IT adoption decisions. During our study period, the health information society surveyed nearly all nonfederal, acute care U.S. hospitals, although small rural hospitals were underrepresented.

Finally, the Centers for Medicare and Medicaid Services (CMS) Hospital Compare database provides process-quality measures. Hospital Compare includes nearly all nonfederal, acute care U.S. hospitals, with the notable exception of some Critical Access Hospitals (rural facilities with twenty-five or fewer beds). These samples were largely matched by Medicare provider identification numbers, with confirmation based on facility names and addresses. Our analytic sample includes more than 70 percent of nonfederal, acute care U.S. hospitals, with small rural institutions (such as Critical Access Hospitals) underrepresented.

▸ **DEFINITIONS:** We focused on two health IT applications described in the HIMSS data: electronic health records and computerized physician order entry. Following Kateryna Fonkych and Roger Taylor,[16] we defined an *electronic health record* as a set of applications including a computerized patient record with a clinical data repository and some clinical decision-support capabilities. Clinical decision support provides treatment recommendations based on patient-specific clinical information and treatment guidelines. It is most frequently used to help physicians make medication decisions.

Computerized physician order entry is an application that assists physicians in generating and accessing orders for prescriptions, laboratory tests, and other medical services. We defined *health IT* as an indicator variable equal to 1 for hospitals that have both electronic health records and computerized physician order entry and 0 otherwise.

This measure differs notably from that described by Ashish Jha and colleagues.[17] Their definition of *comprehensive electronic health record systems* describes relatively sophisticated health IT systems with thorough implementation. Although Jha and colleagues establish an important standard for leading systems with this definition, only 1.5 percent of hospitals have comprehensive systems.

Our definition is intended to focus on the average adopter rather than the leading adopter. In our discussion, we further address the potential consequences of differences in these measures.

Exhibit 1 illustrates the prevalence of health IT across time for both academic and nonacademic hospitals. We defined *academic hospitals* as members of the Council of Teaching Hospitals. The distinction between academic and nonacademic hospitals is important to our final set of analyses.

▶ **HOSPITAL CHARACTERISTICS:** These adoption trends are largely driven by hospitals that already had electronic health records and then adopted computerized physician order entry.[18] We also controlled for a variety of hospital characteristics that might influence process quality. Specific variables include the number of adjusted admissions (the AHA's measure of inpatient and outpatient volume that adjusts for resource utilization);[19] the percentage of discharges covered by Medicare; the percentage of discharges covered by Medicaid; the number of registered nurse full-time equivalents per staffed bed; academic status (Council of Teaching Hospitals membership); and multihospital system membership. Sample means and standard deviations are described in Table 1 in the online Technical Appendix.[20]

▶ **PROCESS-QUALITY MEASURES:** Finally, we used six process-quality measures from the CMS Hospital Compare database. Before conducting our analysis, we selected a subset of quality measures on the basis of three criteria that would minimize bias attributable to measurement error.

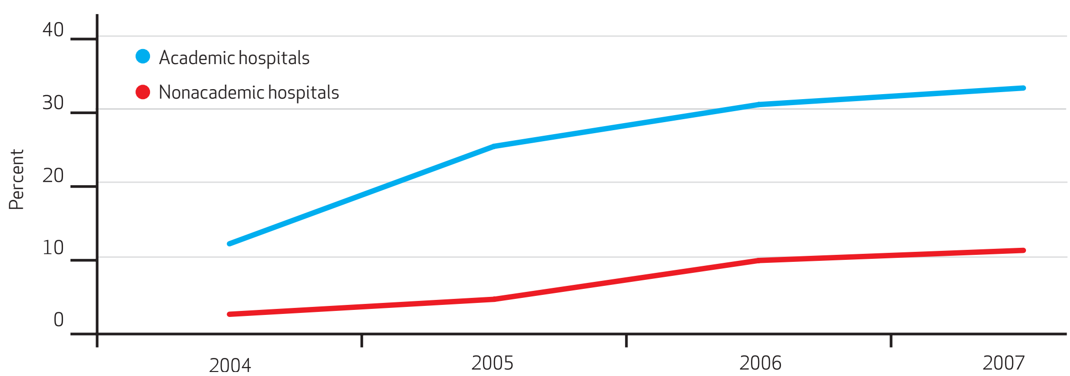
First, reporting needed to be both prevalent and consistent across time.[21] For example, we excluded surgical quality measures, because both the numbers of reporting hospitals and the sample means changed dramatically across time. Second, hospitals in the sample must report a substantial number of cases. We excluded, for example, acute myocardial infarction measures, because these data are based on relatively few cases in rural hospitals. Finally, the measures must be plausibly influenced by electronic health records or computerized physician order entry.

We identified relationships between process-quality measures and health IT systems through consultations with a wide range of experts, including physicians, nurses, and other providers; administrators; and health informatics practitioners and consultants.

Ultimately, we focused on six process-quality measures. These included the percentage of heart failure patients given an angiotensin-converting enzyme (ACE) inhibitor or angiotensin II receptor blocker (ARB) for left ventricular systolic dysfunction; the percentage of smokers with heart failure and pneumonia, respectively, who were given smoking cessation advice; the percentage of pneumonia patients

EXHIBIT 1

Proportion Of Hospitals With Both Electronic Health Records And Computerized Physician Order Entry, By Academic Status, 2004–2007



SOURCE Health Information and Management Systems Society (HIMSS) Analytics database. **NOTES** *Adoption* is defined as having adopted both types of technology. These trends effectively describe hospitals with electronic health record adoption and computerized physician order entry.

assessed and given pneumococcal vaccination if indicated; the percentage of pneumonia patients whose initial blood culture in the emergency department preceded their first dose of hospital-administered antibiotics; and the percentage of pneumonia patients given the most appropriate initial antibiotic.

These quality measures largely reflect the quality of hospitals' medication administration processes. Both computerized physician order entry and electronic health records are designed to capture and communicate information relevant to medication prescribing and delivery. We would have liked to study medication errors directly, but the necessary data are not available in a national panel. The means, standard deviations, and sample sizes of these measures are described in Table 1 of the online Technical Appendix.[20]

METHODS

▶ **MULTIVARIATE REGRESSION:** We used multivariate regression techniques to measure the effect of health IT on each quality measure independently.[22] In each case, we regressed the quality measure on health IT adoption, lagged by one year—in effect, calculating average quality in the span of time following the year after adoption. The regressions also included a hospital-specific fixed effect (a separate indicator variable for each hospital), a time-specific fixed effect, and a set of time-varying hospital controls.

The health IT variable was lagged because the returns from adoption might not be immediately realized.[23] Hospital-specific controls included adjusted admissions, percentage of Medicare discharges, percentage of Medicaid discharges, and registered nurse full-time equivalents per bed. Time-invariant controls (for example, rural versus urban, for-profit ownership, and so on) were not included, because they were captured by the fixed effect.

▶ **SELECTION BIAS:** Because these data are observational, we were concerned that selection bias in health IT adoption might affect our results. Health IT adoption may, for example, be more prevalent among otherwise high-quality hospitals. This would cause cross-sectional regressions to overestimate the effect of health IT on quality. Alternatively, otherwise low-quality hospitals might adopt health IT to improve their performance. This would cause cross-sectional regressions to underestimate the effect of health IT on quality.

We mitigated these potential sources of selection bias by including both hospital- and time-specific fixed effects in our regressions. Fixed effects were implemented by including a separate indicator variable for each hospital and each year in the regression. Thus, we measured the change in quality with health IT adoption within individual hospitals. Although this approach improved the quality of the analysis, we discuss potential limitations below. Further discussion of methods is available in the online Technical Appendix.[20]

Study Results

Each row of Exhibit 2 presents the results from one regression. The first column describes the average quality across all hospitals in the sample in the absence of electronic health records and computerized physician order entry. The second column describes hospitals' average quality mea-

EXHIBIT 2

Regression Results For The Effect Of Computerized Physician Order Entry And Electronic Health Records On Process Quality In All Sampled Hospitals, 2004–7

Process-of-care measure	No health IT (%)	Health IT (%)	Difference in quality after health IT adopted (percentage points)
HEART FAILURE PATIENTS			
ACE inhibitor/ARB use	83	84	0.4
Smoking cessation advice	84	85	0.3
PNEUMONIA PATIENTS			
Pneumococcal vaccination	69	71	2.1**
Blood culture preceded antibiotic	86	86	0.2
Smoking cessation advice	77	78	1.7
Most appropriate antibiotic	79	81	1.3***

SOURCE Authors' analysis based on data from Health Information and Management Systems Society (HIMSS) Analytics; Hospital Compare, Centers for Medicare and Medicaid Services; and the American Hospital Association annual survey. **NOTES** IT is information technology. ACE is angiotensin-converting enzyme. ARB is angiotensin II receptor blocker. Sample sizes correspond to the number of reporting hospitals (see Table 1 in the online Technical Appendix, available by clicking on the Technical Appendix link in the box to the right of the article online) for a given quality measure. Standard errors are clustered by hospital to correct for repeated observations on hospitals and robust to heteroskedasticity. $^{**}p = 0.05$ $^{***}p = 0.01$

sures with health IT. Each of these numbers controls for differences in observed hospital characteristics.

The third column describes the average difference in quality measures that followed health IT adoption. The effects of control variables are omitted for brevity.

For nearly all measures, average quality was higher for hospitals with electronic health records and computerized physician order entry. However, this difference was statistically significant only for pneumococcal vaccine administration and use of the most appropriate antibiotic for pneumonia. In those cases, health IT was associated with a 2.1-percentage-point increase and a 1.3-percentage-point increase, respectively.

These results suggest that health IT has small but positive effects on the quality metrics that we can measure across a wide range of U.S. hospitals. These should not, however, be interpreted as comprehensive measures of health IT value. Rather, we measured the average effect of health IT in only six dimensions. Health IT may well improve other aspects of quality unmeasured by our data.

Our qualitative interviews with clinicians and health IT experts suggested that there might be a pattern regarding which quality measures are affected by combined electronic health records and computerized physician order entry. Decisions regarding pneumococcal vaccination and the use of the most appropriate antibiotic for pneumonia patients are relatively straightforward—health IT serves as a reminder. Conversely, use of ACE inhibitors and ARBs and blood culture preceding antibiotic use are more complicated decisions for which clinicians might be less willing to rely on decision-support algorithms.

ACADEMIC VERSUS NONACADEMIC SETTINGS The effect of health IT on quality undoubtedly varies across hospitals. There are many potential sources of this variation, such as the leadership and skill of each hospital's personnel. Although idiosyncratic differences in practice or management can affect quality, we were interested in systematic differences in types of hospitals. Accordingly, we focused on whether health IT value differed for academic and nonacademic hospitals.

Academic hospitals have been the leading adopters of health IT and the setting for much of the health IT value literature. Academic hospitals also differ from other hospitals in their case-mix and organization. Consequently, it is crucial that we understand whether and how the academic context influences health IT value.[24]

Focusing on academic hospitals only, with the same series of analyses, we found larger and more significant effects of health IT adoption (Exhibit 3). For each measure, the difference in quality following health IT adoption was larger than it was for hospitals on average. The improvements were significant for pneumococcal vaccine administration (6.1 percentage points) and the most appropriate initial antibiotic use (3.7 percentage points). The effects of health IT for academic hospitals were about threefold larger than the effects for hospitals on average.

Health IT is correlated with quality improve-

EXHIBIT 3

Regression Results For The Effect Of Computerized Physician Order Entry And Electronic Health Records On Process Quality In Sampled Academic Hospitals, 2004–7

Process-of-care measure	No health IT (%)	Health IT (%)	Difference in quality after health IT adopted (percentage points)
HEART FAILURE PATIENTS			
ACE inhibitor/ARB use	84	85	1.1
Smoking cessation advice	85	87	1.6
PNEUMONIA PATIENTS			
Pneumococcal vaccination	81	87	6.1**
Blood culture precedes antibiotic	85	86	0.5
Smoking cessation advice	78	81	3.4
Most appropriate antibiotic	85	88	3.7**

SOURCE Authors' analysis based on data from Health Information and Management Systems Society (HIMSS) Analytics; Hospital Compare, Centers for Medicare and Medicaid Services; and the American Hospital Association annual survey. **NOTES** IT is information technology. ACE is angiotensin-converting enzyme. ARB is angiotensin II receptor blocker. Sample sizes correspond to the number of reporting hospitals (see Table 1 in the online Technical Appendix, available by clicking on the Technical Appendix link in the box to the right of the article online) for a given quality measure. Models were estimated using all observations, but these predictions are for academic institutions ($N \approx 272$). Standard errors are clustered by hospital to correct for repeated observations on hospitals and robust to heteroskedasticity. $^{**}p = 0.05$

ment in nonacademic hospitals (Exhibit 4). Although positive for each measure, the differences are small and not statistically significant.

STUDY LIMITATIONS These results help inform our understanding of how health IT influences quality; however, they do have important limitations. First, we did not study all of health IT's potential benefits. Second, we did not track important variations in the individual hospitals' health IT investments. Although we designed our empirical strategy to mitigate bias stemming from these omitted variables, the topic deserves further scrutiny.

Discussion

Our results suggest that recent returns from health IT have largely accrued to academic medical centers. Because we focused on differences following adoption, we did not compare adoption at average U.S. hospitals to that in the very leading academic institutions that would have adopted health IT before our study period began. Rather, we compared the change in quality following new electronic health record and computerized physician order entry adoptions in different settings. (Academic institutions with a long history of health IT investment may well be reaping larger benefits.)

DEPENDENCE ON CONTEXT These results suggest that apparently similar adoptions generate heterogeneous returns across hospitals. One possible explanation is that academic institutions adopt more sophisticated electronic health record and computerized physician order entry systems.

An alternative hypothesis is that health IT value is truly context-dependent. Thus, electronic health records and computerized physician order entry may be more valuable for patients with multiple comorbidities and greater illness severity. These patients, therefore, would require coordination by many physicians ordering a variety of prescriptions and lab tests. Although we found evidence of small returns among nonacademic hospitals, the realization of large-scale benefits may be difficult to generate in many health care settings.

Our primary finding—that health IT value is context-dependent, with larger effects in academic hospitals—has implications for federal health IT policy, and in particular for subsidies and reimbursements to be provided by ARRA.

Broadly speaking, the context dependence we observed has two alternative policy interpretations. First, the difference between academic and nonacademic settings may reflect unobserved variation in the extent and sophistication of technology installed at various institutions. It is likely that academic institutions adopt more sophisticated electronic health record and computerized physician order entry systems with greater functionality and training for both clinical and technical staff. If our context-dependence findings are primarily based on these differences, then we would expect the returns from health IT to grow as adoption and use of health IT spread.

If context dependence is caused by differences in technology and implementation, then the average U.S. hospital will generate large returns only when it fully implements comprehensive

EXHIBIT 4

Regression Results For The Effect Of Computerized Physician Order Entry And Electronic Health Records On Process Quality In Sampled Nonacademic Hospitals, 2004–7

Process-of-care measure	No health IT (%)	Health IT (%)	Difference in quality after health IT adopted (percentage points)
HEART FAILURE PATIENTS			
ACE inhibitor/ARB use	83	84	0.2
Smoking cessation advice	84	84	0.0
PNEUMONIA PATIENTS			
Pneumococcal vaccination	67	68	1.1
Blood culture precedes antibiotic	86	86	0.1
Smoking cessation advice	76	78	1.3
Most appropriate antibiotic	79	79	0.7

SOURCE Authors' analysis based on data from Health Information and Management Systems Society (HIMSS) Analytics; Hospital Compare, Centers for Medicare and Medicaid Services; and the American Hospital Association annual survey. **NOTES** IT is information technology. ACE is angiotensin-converting enzyme. ARB is angiotensin II receptor blocker. Sample sizes correspond to the number of reporting hospitals (see Table 1 in the online Technical Appendix, available by clicking on the Technical Appendix link in the box to the right of the article online) for a given quality measure. Models were estimated using all observations, but these predictions are for nonacademic institutions (N ≈ 3,129). Standard errors are clustered by hospital to correct for repeated observations on hospitals and robust to heteroskedasticity.

This is an area where markets might benefit from increased government intervention.

electronic health record systems. Under these conditions, stringent "meaningful use" criteria—the threshold for qualifying for federal subsidies—will be essential to generating widespread returns from health IT. If the meaningful-use threshold is set low, we should not expect substantive returns from widespread health IT adoption.

An alternative interpretation is that health IT value depends not only on the installed technology but on the setting as well. There are a variety of mechanisms through which the same technology might produce less value in nonacademic settings than in academic ones. Health IT could, for example, be more valuable in coordinating care for patients with more complications seeing multiple specialists and needing multiple lab tests, images, and prescriptions than for the less severely ill patients typically seen outside academic hospitals.

The physician-hospital relationship is also different in academic settings, where physicians are more likely to be integrated (for example, to have exclusive or even employment-based relationships with hospitals). Physician-hospital integration may facilitate the selection and implementation of decision-support capabilities. Furthermore, integrated physicians might have stronger incentives to use health IT in both inpatient and outpatient settings.

If the academic setting or patient population is intrinsic to health IT value, we would expect health IT in nonacademic settings to generate less value than in academic settings. This difference would persist even as technological sophistication, and possibly utilization, increased. Under these conditions, we would not expect policies that induce widespread adoption to yield substantial quality improvements.

FOCUSING ON THE NONACADEMIC SETTING Under these circumstances, policies focused on improving the efficacy of health IT in nonacademic environments might be beneficial. There are a number of potential policy alternatives. For example, improved interoperability standards might increase health IT value. Many electronic health record systems have difficulty sharing information. This is an area where markets might benefit from increased government intervention. If physician-hospital integration is the source of context dependence, then increased interoperability or, possibly, information exchanges might improve the value of health IT in nonacademic settings. Alternatively, investments in the evidence base for decision-support protocols might also increase the efficacy of health IT.

Our results suggest that achieving substantive benefits on a national scale may require a lengthy process. Furthermore, if it is to inform policy, the health IT evidence base must go beyond the academic setting. Ideally, our understanding of the nature of context dependence would benefit from combining patient-level data with our empirical strategy. Thus, we could observe whether the effect of health IT depended on patients' or hospitals' characteristics. ■

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18 We present results for the adoption of both electronic health records and computerized physician order entry, but we also tested the effect by itself. The results for computerized physician order entry were consistent with those reported herein.
19 Our results were nearly identical using alternative scale measures such as the number of staffed beds and outpatient visits.
20 The Technical Appendix can be accessed by clicking on the Technical Appendix link in the box to the right of the article online.
21 We avoided measures that had large missing data problems. We also avoided measures for which the number of respondents or response values changed drastically across time, because such variation would likely mask any effect of computerized physician order entry and electronic health records.
22 Formally, we used ordinary least squares. Errors are robust to heteroskedasticity and were clustered to correct for correlation due to repeated observations on the same hospital.
23 We tested, and rejected, alternative lag structures; however, our ability to explore longer lags was limited by the number of years in which Hospital Compare data were collected.
24 We also examined other forms of context dependence such as size and rural versus urban location. We did observe that effects were somewhat higher for large hospitals, but this difference was smaller and less robust than the academic differences were. No significant differences were observed for rural hospitals.