HSR Health Services Research

DOI: 10.1111/j.1475-6773.2012.01441.x
RESEARCH ARTICLE

The Impact of Health Information Technology Adoption by Outpatient Facilities on Pregnancy Outcomes

Mary E. Deily, Tianyan Hu, Sabrina Terrizzi, Shin-Yi Chou, and Chad D. Meyerhoefer

Objective. Examine whether health information technology (HIT) at *nonhospital* facilities (NHFs) improves health outcomes and decreases resource use at *hospitals* within the same heath care network, and whether the impact of HIT varies as providers gain experience using the technologies.

Data Sources. Administrative claims data on 491,832 births in Pennsylvania during 1998–2004 from the Pennsylvania Health Care Cost Containment Council and HIT applications data from the Dorenfest Institute.

Study Design. Fixed-effects regression analysis of the impact of HIT at NHFs on adverse birth outcomes and resource use.

Principal Findings. Greater use of clinical HIT applications by NHFs is associated with reduced incidence of obstetric trauma and preventable complications, as well as longer lengths of stay. In addition, the beneficial effects of HIT increase the longer that technologies have been in use. However, we find no consistent evidence on whether or how nonclinical HIT in NHFs affects either resource use or health outcomes.

Conclusions. Clinical HIT applications at NHFs may reduce the likelihood of adverse birth outcomes, particularly after physicians and staff gain experience using the technologies.

Key Words. HIT, spillovers, learning, nonhospital facilities, pregnancy

Health care in the United States is fragmented, with patients receiving services at different sites and from different specialists (Moore, Wisnivesky, and McGinn 2003; Cebul et al. 2008), so health information technology (HIT) that facilitates coordinated care may produce large gains in quality and efficiency (Institute of Medicine and Committee on Quality of Health Care in America 2001). However, previous research has focused on measuring the impact of HIT adoption by hospitals on average hospital or individual inpatient health outcomes, or on hospital costs or productivity. We extend this literature by determining whether greater use of HIT at *nonhospital* facilities (NHFs) improves pregnancy outcomes at *hospitals* in the same health care network, either directly or through spillovers.

We focus on pregnancy outcomes because deliveries are one of the most common procedures, so improving either health or cost outcomes may have a large impact. Further, because pregnancy episodes typically require women to make multiple visits to inpatient and outpatient facilities over a relatively short-time period, we expect pregnancy outcomes to be particularly sensitive to HIT investments by NHFs that facilitate transitions across care settings. We use a sample of Pennsylvania patients because detailed inpatient data are available that allow us to combine information on HIT in NHFs with extensive controls for individual patients' characteristics and health status.

We find that higher per-facility clinical HIT use by NHFs is associated with lower rates of obstetric trauma and preventable complications, and with longer lengths of stay, at hospitals in the same health care network. Further, the beneficial impacts increase as physicians and staff gain experience with the technologies. However, we find no consistent evidence of whether or how nonclinical HIT adoption by NHFs affects resource use or health outcomes at associated hospitals.

Our findings contribute to the burgeoning literature evaluating the impact of investments in HIT. Although incentives and penalties related to the adoption of electronic medical records (EMRs) have already been established in the United States, policy debate over whether to encourage the adoption of other technologies continues. Furthermore, the criteria for establishing whether EMRs and other HIT investments provide "meaningful use" are still evolving. Information on how technology investments in outpatient facilities impact outcomes in the inpatient setting is important in order for policy makers and regulators to formulate requirements for the level of technology integration across care settings.

Address correspondence to Mary E. Deily, Ph.D., Department of Economics, Lehigh University, 621 Taylor Street, Bethlehem, PA 18015; 610-758-4951; e-mail: med4@lehigh.edu. Tianyan Hu, B.S., are is with the Department of Economics, Lehigh University, Bethlehem, PA. Sabrina Terrizzi, M.S., is with the Department of Economics and Business, Moravian College, Bethlehem, PA. Shin-Yi Chou, Ph.D., and Chad D. Meyerhoefer Ph.D. are is with the Department of Economics, Lehigh University, Bethlehem, PA.

BACKGROUND

Ideally, adopting HIT improves the quality of care while also reducing costs by prompting providers with guidelines, eliminating duplicate tests, reducing medication errors, and improving the flow of clinically relevant information. Yet evidence showing that HIT improves actual health outcomes has been weak. Studies in the medical and medical informatics literatures, most usually confined to single hospitals, tend to focus on whether HIT improves providers' adherence to guidelines, which may or may not improve health outcomes (Kuperman and Gibson 2003; Chaudhry et al. 2006). Some studies do examine the impact on patient outcomes, but many show little or no effect (Garg et al. 2005). However, a review of recent research provides stronger evidence that HIT improves both adherence and outcomes (Buntin et al. 2011).

The economics and the health services literature also provide evidence on the effect of HIT on the quality of care, again generally through its impact on adherence measures but also on actual health outcomes. Miller and Tucker (2011) find that adoption of basic EMRs by hospitals reduces infant mortality, and Yu et al. (2009), Himmelstein, Wright, and Woolhandler (2010), and McCullough et al. (2010) all find that hospital HIT can have a small positive impact on outcomes and process measures.

In the study closest to ours, Parente and McCullough (2009) analyze a national sample of Medicare patients to determine whether three specific HIT applications improved any of three patient safety indicators. They find evidence that only one of the HIT applications, EMRs, could be clearly linked to an improved patient outcome (fewer infections due to medical care). This effect was small, although it appeared to be growing over time.

There is also evidence that HIT may reduce costs and increase productivity. Borzekowski (2009) finds that HIT may reduce hospital operating costs as do Housman et al. (2006), although in the latter case only after a threshold level of investment is attained. Lee et al. (2010) show that HIT is associated with greater productivity, but Furukawa, Raghu, and Shao (2010) find that implementation of HIT in medical-surgical units reduces productivity. Javitt, Rebitzer, and Reisman (2008) find that new decision support HIT used for one group of HMO patients lowered their average charges, while Garrido et al. (2005) report that electronic medical records (EMRs) resulted in fewer ambulatory office visits (see Buntin et al. 2011, for more).

Finally, researchers have looked for spillover effects in several different health care settings: from one doctor to another (Escarce 1996; Burke, Fournier, and Prasad 2007), from HMO patients to non-HMO patients (Baker 1999; Baker and Phibbs 2002), and from for-profit to not-for-profit hospitals (Kessler and McClellan 2002; Horwitz and Nichols 2009). However, researchers have done little to examine how HIT in one provider venue directly affects outcomes in another venue or creates spillovers that affect outcomes in another venue.

CONCEPTUAL FRAMEWORK

HIT applications in NHFs may affect pregnancy outcomes in hospitals because timely access to accurate information from a woman's OB/GYN visits is critical to properly managing her pregnancy on the inpatient unit, particularly for high-risk cases (Miller, Yeast, and Evans 2003; Cherouny et al. 2005; Eden et al. 2008). Some of the technologies adopted by NHFs, such as clinical data repositories, are specifically designed to improve the flow of clinical information across facilities within a health care system, and thereby directly improve care.

Other HIT applications may impact health outcomes through spillover effects. For example, nonhospital HIT may improve hospital outcomes if it improves the care patients receive at NHFs, and as a result, the health status of patients treated at hospitals. Likewise, negative spillovers may occur if, for example, clinicians must reallocate time spent with patients to learning how to use new HIT. Nonhospital HIT may also have positive spillover effects on hospital costs if it reduces the need for duplicative tests or prevents complications that lead to longer stays or more expensive treatments.

Due to complementarities associated with the use of various technologies, the potential for spillover effects may exist even for some HIT applications that are only tangentially related to clinical practice. Nonetheless, we do expect technologies with direct clinical applications to have a larger impact on health outcomes than those used for nonclinical purposes, while nonclinical HIT may have a larger effect on hospital resource use than clinical applications. To allow for different relationships across outcome variables, we develop separate measures of HIT based on clinical and nonclinical applications.

Both spillovers and direct effects of nonhospital HIT are likely to increase over time for clinical and nonclinical applications. Studies of information technology adoption by businesses show that successful implementation requires staff training in addition to work process and organizational change (Barley 1990; Brynjolfsson and Hitt 2000; Sherer, Kohli, and Baron 2003;

Markus 2004; DeVore and Figlioli 2010). Effecting such change can cause short-term reductions in productivity and substitution away from clinical time as staff members learn how to incorporate the new systems into their workflow. Thus, the extent to which HIT adoption by NHFs improves hospital health outcomes and efficiency will likely depend on how long facilities have been using the systems (Devaraj and Kohli 2000; Brynjolfsson and Hitt 2003; Parente and McCullough 2009). Therefore, we include measures of both the amount and the age of HIT adopted by NHFs in our empirical models.

METHODS

We use a fixed-effects linear regression to identify the impact of the level and age of HIT adopted by NHFs on pregnancy outcomes and resource use at hospitals in the same health care system. Our models control for numerous observable characteristics of patients, hospitals, and local health care markets, and for potentially confounding unobserved time-invariant system characteristics and system-specific linear time trends. Our specification is

$$Outcome_{ihst} = \alpha + \beta_1 HIT_{st} + \beta_2 HITAGE_{st} + \beta_3 P_{ihst} + \beta_4 H_{ht} + ST_{st} + \lambda_s + \tau_t + \varepsilon_{ihst},$$

where the dependent variable is the outcome for patient i in hospital h of system s in year t, HIT represents variables that measure the amount of clinical and of nonclinical HIT in NHFs, HITAGE represents variables that measure the average ages of clinical and of nonclinical HIT, P is a vector of patient characteristics, and H is a vector of hospital characteristics. We also include system-specific linear time trends, ST_{st}, and fixed effects for system, λ_s, and year, τ_t.

We do not include controls for HIT installed in the hospital where the delivery takes place, because all Pennsylvanian hospitals in our HIT database reported adopting all the technologies measured in the database. Consequently, there are no differences in the level of HIT adoption at hospitals to confound our estimates of the impact of a system's nonhospital HIT on outcomes. Instead, the variation in HIT for our study comes from differences in the level and age of HIT at NHFs within hospital systems over time.

HIT Variables

Our data on HIT applications in NHFs are drawn from the 1998–2004 HiMSS Analytics™ Database (Health Information Management Systems

Society, Chicago, IL), which contains survey data on the type, number, and year of installation of HIT applications in health care facilities[1] and is the only publicly available source of information about HIT that surveys the same health care providers on an annual basis. The HiMSS data have been used previously for adoption studies (e.g., Borzekowski 2009), and Diana, Kazley, and Menachemi (2011) provide evidence that they are internally consistent.

Crucially for our study, the HiMSS dataset contains information on HIT applications in NHFs that are members of the same "Integrated Healthcare Delivery System" (IHDS) as the hospitals in the survey (those with at least 100 beds) (Fonkych and Taylor 2005). In the HiMSS dataset, an IHDS is defined as a "vertically integrated health care delivery system" comprised of one or more hospitals and its associated NHFs, which include a wide variety of subacute care facilities, ambulatory care, physician offices, clinics, and facilities owned by the provider or payor. (See Appendix S1 for a description of two systems and a list of all NHFs in the HiMSS data.) The facilities in an IHDS may be linked by ownership or contract, but fewer than 1 percent of the NHFs are associated with more than one system in the HiMSS data.[2]

Most HIT studies use a simple count of the number of HIT applications in a given facility as a measure of HIT availability. We follow this convention but divide the total number of NHF applications in a system by the total number of system facilities to calculate a per-facility measure of HIT availability in each system. In calculating our HIT variables, we exclude various NHFs that do not provide treatment to women of child-bearing age (see Appendix).

We calculate two measures of NHF HIT: one for clinical applications and one for nonclinical applications. We follow Borzekowski (2009) in assigning the applications into clinical and nonclinical categories, with the exception of Order Communication/Results, which we include among the clinical applications (see Table 1).

HIT age is the number of years since an application has been installed at a facility. We first computed the average age of the clinical and nonclinical applications within each NHF, and then averaged over all NHFs in the system. Unfortunately, the installation date for an application was frequently missing. If only some applications at a NHF had missing installation dates, we created averages using those applications for which the installation date was reported. (In those cases where some data are missing, the age variable is based, on average, on the ages of 74.4 percent of the clinical applications and 69.7 percent of the nonclinical applications.)

Finally, to make sure that our variable for HIT age does not capture other system-level factors that increase over time, we include system-specific

Table 1: Applications by Categories and Subcategories

Application Category	*Subcategory Name*	*Application Name*
Clinical	Ancillary departments	Emergency department
		Laboratory
		Operating room (OR)
		Pharmacy
		Radiology
	Clinical support	Clinical data repository
		Clinical decision support
		Order communication/results
		Point of care (med/surg bedside term)
Nonclinical	Admin/discharge/transfer	Patient registration
	Administrative	Administrative
		Managed care management (managed care support)
		Materials management
		Nurse staffing
		Personnel administration
	Business decision support	Case mix analysis
		Executive info system
		Flexible budgeting
		Outcomes and quality management
	Finance	Accounts payable
		Benefits administration
		Cost accounting
		Credit/collections
		Electronic claims
		Encoder
		General ledger
		Patient billing
		Payroll
	Medical records	Abstracting
		Chart deficiency
		Chart tracking/locator
		Master patient index
		Transcription

Source for categorization of applications is Borzekowski (2009). See the *HiMSS User Guide and Data Dictionary*, Glossary of Applications for descriptions of each of these applications.

linear time trends in our models. The HIT age variables are separately identified from these time trends because NHFs continually adopt new technologies. We expect HIT age to be positively related to outcomes because the adoption of systems can be disruptive in the short run, and because it takes time for physicians and staff to learn how to fully utilize and extract benefits from the technologies.

Table 2 presents information about the hospital systems and the HIT applications in the NHFs in those systems, both for the full information subsample and the larger sample with missing age data. The data indicate that the average number of HIT applications per system, as well as the average number of facilities per system, is fairly constant over time.

To further explore the sources of variation in our clinical and nonclinical HIT measures, we estimated auxiliary regressions of the annual change in HIT per system facility on the annual changes in the number of HIT applications in the system (the numerator of the ratio) and the number of hospitals and NHFs in the system (the two components of the denominator of the ratio). From these regressions, we computed partial coefficients of determination that indicate the proportion of variation in the per-facility HIT measure explained by each factor, which is not explained by the other two factors. For our measure of clinical HIT per facility, the partial coefficients of determination for the annual changes in clinical applications, the number of hospitals, and the number of NHFs were 0.22, 0.17, and 0.10, respectively, and for our measure of nonclinical HIT per facility, they were 0.27, 0.17, and 0.24, respectively. Therefore, the annual change in clinical and nonclinical applications explains the largest proportion of variation in the change in both of our per-facility measures of HIT.

Sample

Our sample of patients is drawn from the inpatient database collected by the Pennsylvania Health Care Cost Containment Council (PHC4), which contains all women delivering babies during the period 1998–2004 in Pennsylvania hospitals. We exclude pregnancies that did not result in a birth, giving us a sample of 946,824 deliveries in 157 different hospitals during the sample period. Of these, 80,449 observations are omitted from the sample because they correspond either to hospitals with fewer than 100 beds (9 hospitals) or to large hospitals that were not surveyed by HiMSS or the American Hospital Association (17 hospitals).

We omitted an additional 22,828 observations because there was no information on HIT applications, either because there were no applications or the facility did not report them, leaving us a sample of 843,547. Because this sample, which we call our secondary sample, included many observations where only one category of HIT was reported, we decided to include only those systems that report HIT for both categories of applications, as well as their installation dates, leaving a final sample of 491,832 births occurring in 92 different hospitals.[3] However, we also omit the HIT age variables from our

Table 2: Trend of System Characteristics 1998–2004

Variable	*1998*	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*
Primary sample* (N = 491,832)							
Number of systems	42	49	49	53	47	43	44
Average number of all facilities per system	35.976	45.499	44.563	40.921	37.234	37.588	39.479
Average number of hospitals per system	2.741	4.080	4.015	3.934	4.190	4.156	4.184
Average number of NHFs per system	33.235	41.419	40.547	36.987	33.044	33.432	35.295
Median of number of hospitals per system	2	3	3	2	2	2	2
Median of number of NHFs per system	16	29	33	27	26	25	26
Average number of clinical applications per facility per system	0.723	0.509	0.565	0.638	0.643	0.606	0.646
Average number of nonclinical applications per facility per system	3.295	2.956	3.059	3.365	3.329	3.280	3.455
Average age of clinical applications in NHFs per system	6.325	7.071	7.037	7.964	7.737	8.146	8.766
Average age of nonclinical applications in NHFs per system	4.583	5.118	5.542	6.614	6.896	6.886	8.292
Secondary sample* (N = 843,547)							
Number of systems	82	81	81	81	76	76	79
Average number of all facilities per system	32.093	39.238	37.692	34.358	33.219	32.779	33.112
Average number of hospitals per system	2.991	3.552	3.540	3.560	3.427	3.493	3.349
Average number of NHFs per system	29.102	35.686	34.152	30.797	29.792	29.287	29.763
Median of number of hospitals per system	2	2	2	2	2	2	2
Median of number of NHFs per system	15	16	24	20	21	21	23
Average number of clinical applications per facility per system	0.434	0.367	0.363	0.405	0.400	0.363	0.356
Average number of nonclinical applications per facility per system	2.328	2.362	2.286	2.486	2.469	2.340	2.341

*The primary sample includes only those observations occurring at hospital systems where the NHFs report having both clinical and nonclinical applications, and also report installation dates for some or all individual applications. The secondary sample contains observations where no age data are available for any of the HIT applications, as well as observations where only clinical or only nonclinical applications may have been reported.

models and re-estimate them on the secondary sample to ensure that the results found using the smaller primary sample are not a product of a biased selection process reflected in the reporting behavior of NHFs in different systems.

Patient Outcomes

We use diagnosis-related group, current procedural terminology, and International Classification of Disease, 9th revision, clinical classification codes contained in the PHC4 to create indicator variables for measures of obstetric trauma and of preventable complications during delivery; these variables equal one if the adverse outcome occurred, and zero otherwise. We use the definition of obstetric trauma determined in a report for the Agency for Healthcare Research and Quality (McDonald et al. 2002) to be sufficiently validated by previous research. This definition includes trauma to the mother occurring during the birth, such as severe laceration of the cervix or vagina, or other acute injury to pelvic organs.

Our definition of preventable complications includes maternal fever, excessive bleeding, maternal seizure, precipitous labor, prolonged labor, dysfunctional labor, anesthetic complications, fetal distress, rupture of the uterus during labor, and chorioamnionitis. This is a broad measure of adverse events that is likely to be affected by the actions of health care providers (Currie and MacLeod 2008). We are unable to include outcomes such as birth weight or infant mortality because we do not have data on those outcomes.

In addition to health outcomes for mothers, we investigate the impact of HIT on two measures of resource use associated with each pregnancy: the listed total charge for the delivery and the patient's length of stay. Both of these variables have been used in the literature to assess the efficiency impacts of HIT (Tierney et al. 1993; Evans et al. 1998; Chertow et al. 2001), but care must be taken in their interpretation. For example, greater use of HIT may allow providers to better diagnose potential complications during pregnancy, and treat patients more intensively, resulting in higher charges and longer lengths of stay. Alternatively, if HIT use leads to poorer quality care (because, e.g., providers have difficulty accessing information stored electronically), there could be a positive correlation between HIT and both charges and length of stay.

Patient and Hospital Characteristics

We control for patient characteristics with variables that indicate the patient's age category, race or ethnicity, and primary payer type (private insurance, Medicaid, or Medicare). We also include variables to indicate admission from the emergency department, weekend admission, referral by a physician, clinic, or HMO, or transfer from another hospital. We control for type of delivery by including indicator variables for Cesarean section (Henry et al. 1995) and vaginal birth with instruments.

We account for differences in the severity of a patient's condition using indicators for previous Cesarean section, multiple births (e.g., twins), the existence of at least one nonpreventable complication, and the existence of at least one pre-existing condition. Nonpreventable complications include breech delivery, cephalopelvic disproportion, cord prolapse, placenta previa, and abruptio placenta. We define pre-existing conditions as malpresentation, genital herpes simplex virus, diabetes mellitus/abnormal glucose tolerance, hypertensive disorder, oligohydramnios, congenital/acquired abnormality of vagina, other congenital/acquired anomaly, and rhesus (anti-D) isoimmunization.

Our variables for hospital size (number of beds), hospital owner type (not-for-profit or for-profit), whether the hospital is a teaching hospital, and whether the hospital has a level-two or level-three obstetric care unit are from the American Hospital Association *Annual Survey of Hospitals.* (We include a dummy indicating this latter data was missing when hospitals did not report the level of their obstetric care unit.) We also include variables to measure the degree of local competition among hospitals and among insurers. We use the PHC4 data to compute a Herfindahl index (HHI), defined as the sum of hospitals' squared market shares, where market shares are calculated using the variable radius method to define the market area from which the hospital draws 75 percent of its total patients (Phibbs and Robinson 1993; Gresenz, Rogowski, and Escarce 2004). We measure HMO competition using county-level HMO penetration rates, which we obtained from the Pennsylvania Department of Health's *Managed Care Reports.*

Finally, using data from the U.S. Census Bureau, we control for variation in the characteristics of local patient populations by including variables for each county's poverty ratio, median income, and population density.

Time Trends and Fixed Effects

Although we are able to control for numerous observable characteristics of patients, providers, and location, it is possible that there are some important determinants of pregnancy outcomes that we do not observe and that may be correlated with HIT adoption by NHFs. For example, if more progressive hospital systems adopt more HIT and provide better care, then our HIT effects will be overestimated. Alternatively, if unobservably sicker patients tend to seek care at better hospital systems with more HIT, our effects will be underestimated. We control for such unobservable characteristics of health care systems that are time-invariant by including system fixed effects in our models, and for time-varying characteristics of systems using system-specific linear time trends. Finally, we control for aggregate-level characteristics of the health care environment that are constant across systems, but varying over time using year fixed effects.

If, however, the most important unobserved factors are specific to patients rather than health systems, individual mother fixed effects should be included in the model. With mother fixed effects, all of the variation identifying the impact of HIT on outcomes is across mothers who had multiple deliveries during the sample period. Because this is a selected sample, we included system fixed effects in our primary specification and estimated models with mother-level fixed effects to verify that our results are robust to differences in how we mitigate the impact of unobservables.

Table 3 contains descriptive statistics for all these variables, both for the full information subsample and the larger sample with observations missing age data.

RESULTS

Table 4 reports elasticities that represent the percentage change in each outcome corresponding to a 1 percent change in the given HIT variable. The standard errors of the elasticities, reported in parentheses, are clustered at the system level. For each outcome, results for specifications with system fixed effects are reported first, followed by those with both system and mother fixed effects. We focus our discussion on the results with system fixed effects because, although the sign pattern and magnitude of the coefficients are the same when mother fixed effects are included, the estimates are generally less precise.

The results for clinical applications indicate that a 10 percent increase in the number of clinical HIT applications per facility is associated with small but statistically significant reductions in the likelihood of obstetric trauma (.92 percent) and of preventable complications (.83 percent), and a .2 percent increase in length of stay—this latter result may indicate that the HIT allows for more specialized treatment when warranted, with the result of better health outcomes. There is no evidence of a significant effect on total charge. Estimation results for the secondary sample that excludes controls for HIT age also

Table 3: Sample Statistics, 1998–2004

	Primary Sample		*Secondary Sample*	
	Mean	*SD*	*Mean*	*SD*
Dependent variables				
Obstetric trauma	0.098	0.297	0.100	0.300
Preventable complications*	0.095	0.293	0.097	0.296
Total charge, in dollars	6,839.425	6716.785	7436.412	7985.487
Length of stay, in days	2.846	2.523	2.853	2.479
HIT variables				
Number of clinical applications per facility	0.615	0.562	0.383	0.529
Number of nonclinical applications per facility	3.243	2.106	2.372	1.990
Average age of clinical applications	7.592	3.178	4.426	4.461
Average age of nonclinical applications	6.283	3.566	5.684	3.910
Patient characteristics				
Maternal age between 16 and 20	0.126	0.332	0.127	0.333
Maternal age between 21 and 25	0.221	0.415	0.218	0.413
Maternal age between 26 and 30	0.288	0.453	0.283	0.451
Maternal age between 31 and 35	0.246	0.431	0.249	0.433
Maternal age between 36 and 40	0.099	0.299	0.101	0.301
Maternal age between 41 and 45	0.014	0.119	0.015	0.121
Maternal age between 46 and 50	0.000	0.020	0.000	0.021
Maternal age >50	0.000	0.004	0.000	0.004
White-Hispanic	0.026	0.160	0.018	0.133
Black	0.106	0.307	0.118	0.323
Other race, not white	0.119	0.323	0.143	0.350
Medicaid	0.269	0.443	0.274	0.446
Private insurance	0.688	0.463	0.682	0.466
Medicare	0.004	0.066	0.005	0.068
Emergency admission	0.295	0.456	0.372	0.483
Weekend admission	0.252	0.434	0.254	0.435
Patient referred by physician, clinic, or HMO	0.964	0.185	0.968	0.176
Patient transferred from another hospital	0.004	0.066	0.005	0.070
Cesarean section	0.241	0.427	0.239	0.426
Vaginal delivery with instrument	0.102	0.303	0.099	0.299
Previous Cesarean section	0.123	0.328	0.123	0.329
Delivery is a multiple birth	0.017	0.131	0.018	0.134
At least one nonpreventable complication†	0.119	0.324	0.121	0.326
At least one pre-existing condition‡	0.264	0.441	0.271	0.445
Hospital characteristics				
Hospital size (200–400 beds)	0.358	0.479	0.373	0.483
Hospital size (>400 beds)	0.436	0.496	0.392	0.488
Teaching hospital	0.297	0.457	0.320	0.467
Nonprofit hospital	0.998	0.040	0.987	0.114
Hospital obstetrical level is missing	0.072	0.259	0.097	0.296
Hospital obstetrical level = 2	0.302	0.459	0.311	0.463
Hospital obstetrical level = 3	0.385	0.487	0.379	0.485

continued

Table 3. *Continued*

	Primary Sample		*Secondary Sample*	
	Mean	*SD*	*Mean*	*SD*
Hospital HHI	0.524	0.268	0.497	0.286
County characteristics				
HMO penetration rate,%	42.854	12.957	44.346	13.643
Poverty ratio,% population under 100% FPL	10.000	4.068	10.307	4.604
Median income, in $10,000s	4.310	.992	4.335	1.085
Population density, 1,000 people per square mile	1.940	3.235	2.365	3.658
HIT variables by application subcategory				
Ancillary departments, number per facility	0.363	0.358	0.228	0.331
Ancillary departments, average age	8.072	3.742	4.707	4.899
Clinical support, number per NHF	0.252	0.253	0.155	0.230
Clinical support, average age	5.737	4.354	3.345	4.365
Admin/discharge/transfer, number per NHF	0.127	0.115	0.083	0.110
Admin/discharge/transfer, average age	6.845	4.736	4.153	4.969
Administrative, number per NHF	1.145	0.246	1.031	0.269
Administrative, average age	6.142	3.741	5.538	3.993
Business decision support, number per NHF	0.341	0.348	0.217	0.317
Business decision support, average age	6.559	4.626	3.884	4.770
Finance, number per NHF	1.052	0.955	0.679	0.902
Finance, average age	7.305	3.522	4.537	4.521
Medical records, number per NHF	0.578	0.535	0.363	0.503
Medical records, average age	7.044	3.873	4.158	4.551
Sample size	491,832		843,547	

*Preventable complications: maternal fever, excessive bleeding, maternal seizure, precipitous labor, prolonged labor, dysfunctional labor, anesthetic complications, fetal distress, uterine rupture during labor, or chorioamnionitis.
†Nonpreventable complications: breech delivery, cephalopelvic disproportion, cord prolapse, placenta previa, abruption placenta, or premature rupture of membranes.
‡Pre-existing conditions: malpresentation, genital herpes simplex virus, diabetes mellitus or abnormal glucose tolerance, hypertensive disorder, oligohydramnios, congenital or acquired abnormality of vagina, other congenital or acquired abnormality, phesus (anti-D) isoimmunization.

indicate beneficial effects from clinical HIT, although the coefficients are smaller and insignificant in the case of preventable complications.

The results also indicate that a 10 percent increase in the average age of HIT is associated with a 1.03 percent decrease in obstetric trauma and a .76 percent decrease in preventable complications, although the latter effect is not significant. These results imply that, relative to the mean, an additional year of experience is associated with a 1.33 percent reduction in the incidence of obstetric trauma and a .97 percent reduction in the incidence of preventable complications.[4]

We find no evidence that nonclinical NHF HIT reduces charges or shortens lengths of stay at the hospital, nor do we find any effect on prevent-

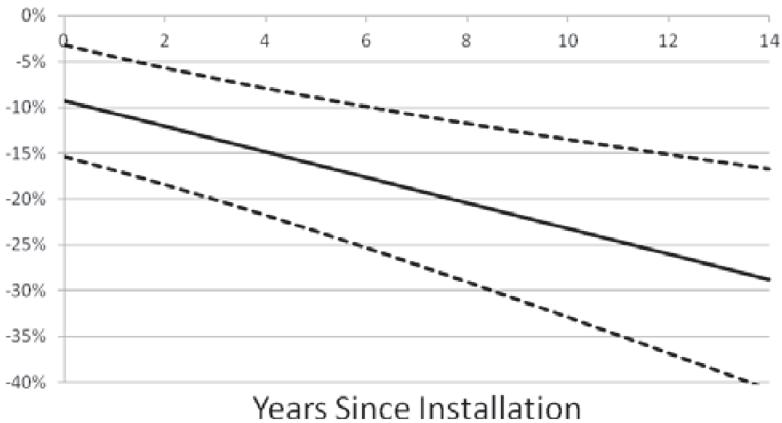
Table 4: Percent Change in Outcome for a One Percent Increase in HIT Variables, by Clinical and Nonclinical Applications†,‡

	Obstetric Trauma		*Preventable Complications*		*Total Charge*		*Length of Stay*§	
Primary sample (N = 491,832)								
Number of clinical applications	−0.092**	−0.088	−0.083**	−0.115	0.011	0.001	0.020**	0.018**
	(0.037)	(0.085)	(0.040)	(0.128)	(0.035)	(0.024)	(0.008)	(0.008)
Average age of clinical applications	−0.103***	−0.054	−0.076	−0.229**	−0.021	−0.050	0.001	0.017**
	(0.033)	(0.050)	(0.057)	(0.093)	(0.058)	(0.067)	(0.010)	(0.008)
Number of nonclinical applications	0.136***	0.058	0.105	0.078	0.011	0.011	−0.015	−0.015
	(0.051)	(0.116)	(0.065)	(0.176)	(0.039)	(0.031)	(0.012)	(0.011)
Average age of nonclinical applications	0.041	0.010	−0.008	0.064	0.029	0.030	−0.007	−0.005
	(0.029)	(0.055)	(0.037)	(0.045)	(0.033)	(0.031)	(0.008)	(0.008)
Secondary sample (N = 843,547)								
Number of clinical applications	−0.049***	−0.056	−0.008	−0.001	0.015	0.012	0.009**	0.010**
	(0.016)	(0.041)	(0.029)	(0.060)	(0.016)	(0.018)	(0.004)	(0.004)
Number of nonclinical applications	0.089***	0.080	−0.001	−0.033	−0.024	−0.023	−0.008	−0.010*
	(0.027)	(0.065)	(0.046)	(0.096)	(0.023)	(0.027)	(0.006)	(0.006)
Fixed effects								
System	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother	No	Yes	No	Yes	No	Yes	No	Yes

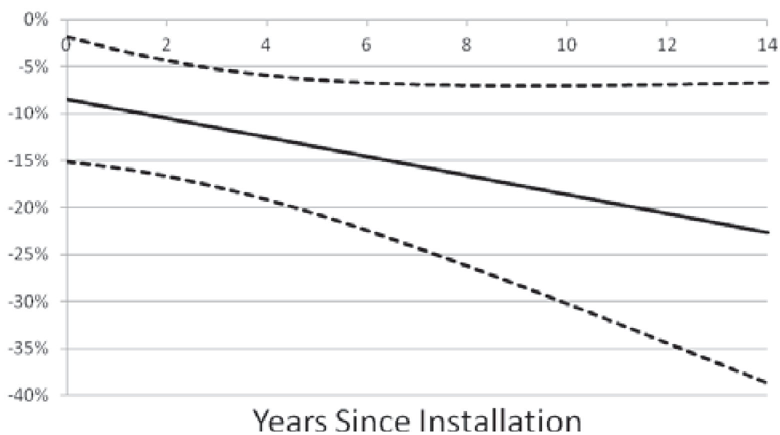
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.
†Dependent variables: obstetric trauma, preventable complications, log of total charge, and log of length of stay. All regressions include the patient, hospital, and hospital county characteristics listed in Table 2, system-specific time trends, and 6-year dummies.
‡Robust standard errors, in parentheses, are clustered by integrated health care delivery system.
§Sample size differs because some observations lacked data for length of stay. For the primary sample, n = 490,686; for the secondary sample, n = 841,617.

Figure 1: Impact of Clinical Technology on Health Outcomes over Time[1]

a. Obstetric Trauma



b. Preventable Complications



Notes. Dashed lines represent the 90% confidence interval, cluster-corrected at the health care system-level.

able complications. However, we do find an unexpected and puzzling result linking nonclinical HIT to increases in obstetric trauma, a result we also find in the estimations without age controls.

Table 5: Percent Change in Outcome for a One Percent Increase in HIT, by Application Subcategory, Primary Sample†,‡

	Obstetric Trauma		*Preventable Complications*		*Total Charge*		*Length of Stay*§	
Clinical applications								
Ancillary departments, number	−0.004	0.030	−0.031	−0.088	−0.021	−0.033	0.006	0.005
	(0.031)	(0.051)	(0.033)	(0.075)	(0.028)	(0.026)	(0.007)	(0.007)
Ancillary departments, age	−0.123***	−0.033	−0.024	−0.097	0.024	0.033	0.010	0.017**
	(0.044)	(0.052)	(0.066)	(0.073)	(0.032)	(0.027)	(0.008)	(0.008)
Clinical support, number	−0.076**	−0.087**	−0.099**	−0.160**	0.016	0.019	0.012**	0.012**
	(0.031)	(0.042)	(0.047)	(0.070)	(0.022)	(0.017)	(0.006)	(0.005)
Clinical support, age	−0.057	−0.078	−0.049	−0.093	−0.012	−0.045	−0.011*	−0.001
	(0.035)	(0.053)	(0.045)	(0.093)	(0.033)	(0.035)	(0.006)	(0.006)
Nonclinical applications								
Admin/discharge/transfer, number	0.009	0.120*	0.171***	0.290***	0.018	0.009	0.011	0.001
	(0.057)	(0.065)	(0.053)	(0.063)	(0.025)	(0.025)	(0.011)	(0.006)
Admin/discharge/transfer, age	0.002	−0.088	−0.044	0.051	0.084	0.078	0.007	−0.011
	(0.042)	(0.063)	(0.072)	(0.090)	(0.051)	(0.048)	(0.009)	(0.008)
Administrative, number	−0.087	−0.055	0.279*	0.321**	−0.212***	−0.144**	−0.007	−0.020
	(0.178)	(0.188)	(0.162)	(0.136)	(0.075)	(0.056)	(0.016)	(0.017)
Administrative, age	−0.013	0.034	0.013	0.063	0.018	0.034	−0.001	0.001
	(0.037)	(0.045)	(0.039)	(0.041)	(0.022)	(0.030)	(0.006)	(0.007)
Business decision support, number	0.060	0.060	0.095*	0.249***	0.127***	0.127***	0.018*	0.005
	(0.048)	(0.085)	(0.050)	(0.073)	(0.040)	(0.038)	(0.009)	(0.015)
Business decision support, age	−0.010	−0.003	0.069	−0.005	−0.119***	−0.058*	0.008	0.021**
	(0.038)	(0.072)	(0.051)	(0.080)	(0.043)	(0.035)	(0.009)	(0.010)
Finance, number	−0.015	−0.222	−0.229**	−0.357**	−0.055	−0.053	0.002	0.000
	(0.123)	(0.151)	(0.105)	(0.156)	(0.060)	(0.051)	(0.019)	(0.016)
Finance, age	0.000	−0.012	−0.049	−0.141	0.040	0.015	0.018*	0.009

continued

Table 5. *Continued*

	Obstetric Trauma		*Preventable Complications*		*Total Charge*		*Length of Stay*[§]	
Medical records, number	0.055	0.099	0.031	−0.024	−0.013	−0.011	−0.035*	−0.009
	(0.079)	(0.109)	(0.062)	(0.090)	(0.054)	(0.043)	(0.018)	(0.017)
Medical records, age	0.067	0.069	0.091	0.066	0.028	0.036	−0.004	0.015
	(0.043)	(0.074)	(0.059)	(0.082)	(0.043)	(0.035)	(0.008)	(0.010)
Fixed effects								
System	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother	No	Yes	No	Yes	No	Yes	No	Yes

***$p < 0.01$;
**$p < 0.05$,
*$p < 0.1$.
†Dependent variables: obstetric trauma, preventable complications, log of total charge, and log of length of stay. All regressions include the patient, hospital, and hospital county characteristics listed in Table 2, system-specific time trends, and 6-year dummies. $N = 491{,}832$.
‡Robust standard errors, in parentheses, are clustered by integrated health care delivery system.
§Sample size differs because some observations lacked data for length of stay. For the primary sample, $n = 490{,}686$; for the secondary sample, $n = 841{,}617$.

We investigated which applications are responsible for the associations of clinical and nonclinical HIT with outcomes by disaggregating the HIT variables into subcategories. Table 5 contains the results of models where the HIT variables are divided into two clinical applications (Ancillary Departments; Clinical Support) and five nonclinical applications (Admin/Discharge/Transfer; Administrative; Business Decision Support; Finance; Medical Records).

We find that the direct health benefits from clinical HIT at NHFs are driven principally by applications in the Clinical Support subcategory, which are associated with less obstetric trauma, fewer preventable complications, and longer lengths of stay, with some evidence that learning may magnify the effects in the case of obstetric trauma. Clinical HIT in the ancillary departments has no immediate significant impact, but benefits may develop with experience.

Alternatively, the results for the disaggregated nonclinical applications give no consistent results. There is some evidence that Administrative HIT is associated with the expected decrease in resource use but also that Business Decision Support HIT is positively correlated with resource use. Further, while the adverse effect of HIT on obstetric trauma disappears, two subcategories of HIT are positively associated with preventable complications, while another has a negative association.

We simulated the effect of the adoption and subsequent use of clinical HIT by NHFs to demonstrate the net impact of HIT on adverse health outcomes over time. First, we define the joint effect of the number of HIT applications per facility and HIT age on the predicted probability of each birth outcome in percentage terms as follows:

$$100 * [\hat{\beta}_1 * \overline{HIT} + \hat{\beta}_2 * HITAGE]/\bar{Y}.$$

Thus, when HITAGE is set to zero the impact on outcomes is the net effect of adopting the average level of per facility HIT (the elasticity times 100). However, as the time since installation of the HIT grows, the impact of HIT on outcomes will vary in accordance with the sign and magnitude of β_2.

Figure 1 shows simulations of the net impact of clinical HIT on health outcomes, relative to outcomes at hospitals in systems with no NHF HIT, as the average number of years since the technologies were installed increases. Hospitals in systems with an initial adoption of the average level of per-facility NHF HIT have a 9.2 percent lower incidence of obstetric trauma and an 8.3

percent lower incidence of preventable complications, and these effects grow over time.

CONCLUSIONS AND LIMITATIONS

We find evidence that greater use of clinical HIT applications by NHFs is associated with lower rates of adverse birth outcomes at hospitals in the same health care network, and that the effects increase over time. We believe the beneficial impact results from direct improvements in information flow from NHFs to hospitals as well as positive spillovers associated with the use of numerous clinical technologies across care settings.

It is less clear that nonclinical HIT in NHFs has an impact on hospital outcomes. It is possible that some type of selection effect may be generating the association of more HIT with worse hospital outcomes, but overall the results were inconsistent and contradictory, giving us little confidence in them.

Our analysis has several limitations that should be kept in mind. We are unable to measure the impact of NHF HIT on outcomes such as birth weight or infant mortality using the PHC4 data. If clinical HIT applications in NHFs improve these outcomes as well, then our estimates will understate the potential health benefits resulting from HIT investments. In addition, our specific findings are limited to the effect of NHF HIT on pregnancy cases. However, the results may have wider implications. Because pregnancy is such a common condition, health care providers are most likely to have developed both formal and informal methods for communicating necessary information among themselves in the absence of HIT. Consequently, NHF HIT may improve care to a greater degree in other situations. For example, the impact may be greater in more complicated cases of chronic disease, such as diabetes, which place similar demands on providers to communicate with each other, but which are less likely to benefit from existing institutions for coordination of care.

Further, although the HiMSS database is the most comprehensive dataset available on HIT installed in health care facilities, it lacks detailed information on the capabilities and quality of the technologies, and on the extent to which technologies have been integrated into facilities' work practices. In addition, correlations among the numbers of applications in the different subcategories are high, suggesting that HIT may be purchased in "bundles," which limits our ability to identify the net effect of specific subcategories of HIT.

Finally, while our models contain fixed effects and system-specific linear time trends, any important unobserved system characteristics that vary nonlinearly over time with both outcomes and HIT will bias our estimates. Future research on the impact of HIT on health outcomes and resource use should focus on the implementation of specific technologies where the installation and training strategy used, characteristics of staff, and degree of administrative integration are directly observable and may be separately evaluated. Nevertheless, our study demonstrates that HIT in NHFs can affect outcomes for patients in associated hospitals, so that any such study should include consideration of system-wide HIT investments.

ACKNOWLEDGMENTS

Joint Acknowledgment/Disclosure Statement: We are grateful for comments and suggestions on earlier versions of this article presented at the 2010 ASHEcon Conference, the 2011 Eastern Economic Association Conference, and at Lehigh University, and for comments and suggestions from the referees and editors of *HSR*. This study received support from the Lehigh Valley Health Network, the Lehigh University College of Business and Economics, the Lehigh University Martindale Center for Private Enterprise, a 2010 Lehigh University Faculty Innovation Grant, and AHRQ Grant PAR-08-270. Data on HIT were provided gratis by The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation, Chicago, Illinois. None of these entities played any role in the design or implementation of this analysis. Data on Pennsylvania inpatients are from the Pennsylvania Health Care Cost Containment Council (PHC4). PHC4 is an independent state agency responsible for addressing the problem of escalating health costs, ensuring the quality of health care, and increasing access to health care for all citizens regardless of ability to pay. PHC4 has provided data in an effort to further its mission of educating the public and containing health care costs in Pennsylvania. PHC4, its agents and staff, have made no representation, guarantee, or warranty, express or implied, that the data—financial, patient, payer, and physician specific information—provided are error-free, or that the use of the data will avoid differences in opinion or interpretation. This analysis was not prepared by PHC4. PHC4, its agents and staff, bear no responsibility or liability for the results of the analysis, which are solely the opinion of the authors.

Disclosures: None.

Disclaimers: None.

NOTES

1. Two additional years of data were available at the time the study was conducted, but the data were collected using a different survey methodology and are not fully comparable to data from the 1998 to 2004 surveys.
2. Those few NHFs associated with more than one IHDS are assigned to two different systems in our data.
3. While we cannot be sure that patients giving birth at a system hospital also received care from the system NHFs, one system reported that over 95 percent of the deliveries in its hospital were by patients that used system NHFs. Unfortunately, we are unable to speculate as to how our results might be affected by those women in the sample who did not receive prenatal care at the system's NHFs as the bias would be a function of how technology adoption at the NHFs where they did seek treatment affected their care.
4. Annual percentage change is $[(\partial Y/\partial HITAGE)/(\bar{Y})] * 100 = [(\hat{\beta}_2 * \overline{HITAGE})/(\bar{Y})] * 100$.

REFERENCES

American Hospital Association. 1998-2004. *Annual Survey Database™*. Chicago, IL: Health Forum LLC, an American Hospital Association Company.

Baker, L. C.. 1999. "Association of Managed Care Market Share and Health Expenditures for Fee-for-Service Medicare Patients." *Journal of the American Medical Association* 281 (5): 432–7.

Baker, L. C., and C. S. Phibbs. 2002. "Managed Care, Technology Adoption, and Health Care: The Adoption of Neonatal Intensive Care." *RAND Journal of Economics* 33 (3): 524–48.

Barley, S. R.. 1990. "The Alignment of Technology and Structure through Roles and Networks." *Administrative Science Quarterly* 35: 61–103.

Borzekowski, R.. 2009. "Measuring the Cost Impact of Hospital Information Systems: 1987–1994." *Journal of Health Economics* 28: 938–49.

Brynjolfsson, E., and L. M. Hitt. 2000. "Beyond Computation: Information Technology, Organizational Transformation and Business Performance." *Journal of Economic Perspectives* 14 (4): 23–48.

———. 2003. "Computing Productivity: Firm-Level Evidence." *Review of Economics and Statistics* 85 (4): 793–808.

Buntin, M. B., M. F. Burke, M. C. Hoaglin, and D. Blumenthal. 2011. "The Benefits of Health Information Technology: A Review of the Recent Literature Shows Predominantly Positive Results." *Health Affairs* 30 (3, March): 464–71.

Burke, M. A., G. M. Fournier, and K. Prasad. 2007. "The Diffusion of a Medical Innovation: Is Success in the Stars?" *Southern Economic Journal* 73 (3): 588–603.

Cebul, R. D., J. B. Rebitzer, L. J. Taylor, and M. E. Votruba. 2008. "Organizational Fragmentation and Care Quality in the US Healthcare System." *Journal of Economic Perspectives* 22 (4): 93–113.

Chaudhry, B., J. Wang, S. Wu, M. Maglione, W. Mojica, E. Roth, S. C. Morton, and P. G. Shekelle. 2006. "Systematic Review: Impact of Health Information Technology on Quality, Efficiency, and Costs of Medical Care." *Annals of Internal Medicine* 144 (10): 742–52.

Cherouny, P., F. Federico, C. Haraden, S. Leavitt Gullo, and R. Resar. 2005. *Idealized Design of Perinatal Care.* IHI Innovation Series White Paper. Cambridge MA: Institute for Healthcare Improvement.

Chertow, G. M., J. Lee, G. J. Kuperman, E. Burdick, J. Horsky, D. L. Seger, R. Lee, A. Mekala, J. Song, A. L. Komaroff, and D. W. Bates. 2001. "Guided Medication Dosing for Inpatients with Renal Insufficiency." *Journal of the American Medical Association* 286 (22): 2839–44.

Currie, J., and W. B. MacLeod. 2008. "First Do No Harm? Tort Reform and Birth Outcomes." *Quarterly Journal of Economics* 123 (2): 795–830.

Devaraj, S., and R. Kohli. 2000. "Information Technology Payoff in the Health-Care Industry: A Longitudinal Study." *Journal of Management Information Systems* 16 (4): 41–67.

DeVore, S., and K. Figlioli. 2010. "Lessons Premier Hospitals Learned about Implementing Electronic Health Records." *Health Affairs* 29: 664.

Diana, M., A. S. Kazley, and N. Menachemi. 2011. "An Assessment of Health Care Information and Management Systems Society and Leapfrog Data on Computerized Provider Order Entry." *Health Services Research* 46 (5): 1575–91.

Eden, K. B., R. Messina, H. Li, P. Osterweil, C. R. Henderson, and J. M. Guise. 2008. "Examining the Value of Electronic Health Records on Labor and Delivery." *American Journal of Obstetrics and Gynecology* 199: 307–307.

Escarce, J. J. 1996. "Externalities in Hospitals and Physician Adoption of a New Surgical Technology: An Exploratory Analysis." *Journal of Health Economics* 15: 715–34.

Evans, R. S., S. L. Pestotnik, D. C. Classen, T. P. Clemmer, L. K. Weaver, J. F. Orme, Jr., J. F. Lloyd, and J. P. Burke. 1998. "A Computer-Assisted Management Program for Antibiotics and Other Antiinfective Agents." *New England Journal of Medicine* 338 (4): 232–8.

Fonkych, K., and R. Taylor. 2005. *The State and Pattern of Health Information Technology Adoption.* Santa Monica, CA: Rand Corporation.

Furukawa, M. F., T. S. Raghu, and B. B. M. Shao. 2010. "Electronic Medical Records and Cost Efficiency in Hospital Medical-Surgical Units." *Inquiry* 47 (Summer): 110–23.

Garg, A. X., H. K. J. Adhikari, H. McDonald, M. P. Rosas-Arellano, P. J. Devereaux, J. Beyene, J. Sam, and R. B. Haynes. 2005. "Effects of Computerized Clinical Decision Support Systems on Practitioner Performance and Patient Outcomes: A Systematic Review." *Journal of the American Medical Association* 293 (10): 1223–38.

Garrido, T., L. Jamieson, Y. Zhou, A. Wiesenthal, and L. Liang. 2005. "Effect of Electronic Health Records in Ambulatory Care: Retrospective, Serial, Cross Sectional Study." *British Medical Journal* 330 (March): 581.

Gresenz, C. R., J. Rogowski, and J. J. Escarce. 2004. "Updated Variable-Radius Measures of Hospital Competition." *Health Services Research* 39 (2): 417–30.

Henry, O. A., K. D. Gregory, C. J. Hobel, and L. D. Platt. 1995. "Using ICD-9 Codes to Identify Indications for Primary and Repeat Cesarean Sections: Agreement with Clinical Records." *American Journal of Public Health* 85 (8): 1143–6.

Himmelstein, D. U., A. Wright, and S. Woolhandler. 2010. "Hospital Computing and the Costs and Quality of Care: A National Study." *American Journal of Medicine* 123 (1): 40–6.

Horwitz, J. R., and A. Nichols. 2009. "Hospital Ownership and Medical Services: Market Mix, Spillover Effects, and Nonprofit Objectives." *Journal of Health Economics* 28: 924–37.

Housman, M. G., L. M. Hitt, K. Z. Elo, and N. Beard. 2006. "The Effect of IT Capital on Hospital Efficiency." Paper presented at the Workshop on Information Systems and Economics (WISE 2006), December 9-10, Northwestern University, Evanston, IL.

Institute of Medicine and Committee on Quality of Health Care in America. 2001. *Crossing the Quality Chasm: A New Health System for the 21st Century.* Washington, DC: National Academy Press.

Javitt, J. C., J. B. Rebitzer, and L. Reisman. 2008. "Information Technology and Medical Missteps: Evidence from a Randomized Trial." *Journal of Health Economics* 27: 585–602.

Kessler, D. P., and M. B. McClellan. 2002. "The Effects of Hospital Ownership on Medical Productivity." *RAND Journal of Economics* 33 (3): 488–506.

Kuperman, G. J., and R. F. Gibson. 2003. "Computer Physician Order Entry: Benefits, Costs, and Issues." *Annals of Internal Medicine* 139 (1): 31–9.

Lee, J., J. S. McCullough, and R. J. Town. 2010. "The Impact of Health Information Technology Adoption on Hospital Productivity." NBER Working Paper #18025. Cambridge, MA: National Bureau of Economic Research.

Markus, M. L.. 2004. "Technochange Management: Using IT to Drive Organizational Change." *Journal of Information Technology* 19: 4–20.

McCullough, J. S., M. Casey, I. Moscovice, and S. Prasad. 2010. "The Effect of Health Information Technology on Quality in U.S. Hospitals." *Health Affairs* 29 (4): 647–54.

McDonald, K., P. Romano, J. Geppert, S. M. Davies, B. W. Duncan, and K. G. Shojania. 2002. *Measures of Patient Safety Based on Hospital Administrative Data-The Patient Safety Indicators.* Technical Review 5 (Prepared by the University of California San Francisco- Stanford Evidence-Based Practice Center, Contract No. 290-97-0013). AHRQ Publication No. 02-0038. Rockville, MD: Agency for Healthcare Research and Quality. August.

Miller, A. R., and C. E. Tucker. 2011. "Can Health Care Information Technology Save Babies?" *Journal of Political Economy* 119 (2, April): 289–324.

Miller, D. W., J. D. Yeast, and R. L. Evans. 2003. "The Unavailability of Prenatal Records at Hospital Presentation." *Obstetrics and Gynecology-New York* 101: 87.

Moore, C., J. Wisnivesky, and T. McGinn. 2003. "Medical Errors Related to Discontinuity of Care from an Inpatient to an Outpatient Setting." *Journal of General Internal Medicine* 18 (8): 646–51.

Parente, S. T., and J. S. McCullough. 2009. "Health Information Technology and Patient Safety: Evidence from Panel Data." *Health Affairs* 28 (2): 357–60.

Pennsylvania Department of Health. 1998-2004. "Managed Care Reports." Available at: http://www.portal.health.state.pa.us/portal/server.pt/community/managed_care/14157/managed_care_reports/558454

Phibbs, C. S., and J. C. Robinson. 1993. "A Variable-Radius Measure of Local Hospital Market Structure." *Health Services Research* 28 (3): 313–24.

Sherer, S., R. Kohli, and A. Baron. 2003. "Complementary Investment in Change Management and IT Investment Payoff." *Information Systems Frontiers* 5: 321–33.

Tierney, W. M., M. E. Miller, J. M. Overhage, and C. J. McDonald. 1993. "Physician Inpatient Order Writing on Microcomputer Workstations: Effects on Resource Utiltization." *Journal of the American Medical Association* 269 (3): 379–83.

United States Census Bureau. 1998-2004. "Model-based Small Area Income & Poverty Estimates (SAIPE) for School Districts, Counties, and States." Available at http://www.census.gov/did/www/saipe/index.html

Yu, F. B., N. Meachemi, E. S. Berner, J. J. Allison, N. W. Weissman, and T. K. Houston. 2009. "Full Implementation of Computerized Physician Order Entry and Medication-Related Quality Outcomes: A Study of 3364 Hospitals." *American Journal of Medical Quality* 24 (4): 278–86.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.
Appendix S1: Systems and Nonhospital Facilities.

Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting materials supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.