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HHS Public Access

Author manuscript

J Health Econ. Author manuscript; available in PMC 2015 April 30.

Published in final edited form as:

J Health Econ. 2014 March ; 34: 19–30. doi:10.1016/j.jhealeco.2013.12.005.

The Effects of Health Information Technology on the Costs and Quality of Medical Care

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Abstract

Information technology has been linked to productivity growth in a wide variety of sectors, and health information technology (HIT) is a leading example of an innovation with the potential to transform industry-wide productivity. This paper analyzes the impact of health information technology (HIT) on the quality and intensity of medical care. Using Medicare claims data from 1998-2005, I estimate the effects of early investment in HIT by exploiting variation in hospitals' adoption statuses over time, analyzing 2.5 million inpatient admissions across 3900 hospitals. HIT is associated with a 1.3 percent increase in billed charges (p-value: 5.6%), and there is no evidence of cost savings even five years after adoption. Additionally, HIT adoption appears to have little impact on the quality of care, measured by patient mortality, adverse drug events, and readmission rates.

Keywords

health information technology; hospital productivity

Technology adoption, and information technology in particular, have been linked to productivity growth in a wide variety of sectors. However, a historical perspective suggests caution is warranted in linking any particular technology to the promise of substantial, sustained productivity growth within a specific industry. Work by the McKinsey Global Institute (2002) argues that the productivity acceleration of the 1990s, widely attributed to information technology (IT), was concentrated in a limited number of sectors, and IT was only one of several factors that combined to create the productivity jump.

In this paper, I analyze the impact of health information technology (HIT) on the costs and quality of medical care, testing whether the technology has demonstrated potential to improve the productivity of the health care sector. Against a backdrop of persistently high growth in health spending, many policymakers are looking to HIT as a key tool to improve the efficiency of the health care sector, by preventing medical errors, cutting redundant tests,

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and improving health outcomes. The RAND Institute has projected that HIT will spur a $142–$371 billion per year reduction in health spending (Hillestad et al. 2005).

The Health Information Management Systems Society estimates that hospitals will spend approximately $26 billion dollars on IT applications between 2010-2014 (HIMSS Analytics 2009). These expenditures will be driven partly by a federal program, the 2009 HITECH Act, which will implement reimbursement incentives and penalties designed to encourage HIT adoption. These new incentive payments are projected to increase net Medicare and Medicaid spending by $30 billion over nine years (2011-2019). However, the Congressional Budget Office (2008) estimates the total costs of the legislation to be markedly lower, $19 billion, since it predicts that HIT will reduce medical expenditures and thus reduce related federal spending.

This study focuses primarily on two types of health information technology: electronic medical records (EMR) and clinical decision support (CDS). EMR maintain patient information and physician notes in a computerized database rather than a paper chart. EMR allow the provider to track the patient's health over time and read the input of other consulting physicians. CDS provides timely reminders and information to doctors. CDS may recommend screening tests, flag drug-drug interactions and drug allergy information, or discourage the provider from repeating a test by highlighting a previous result. Together, these systems form the backbone of a basic clinical HIT system.

The paper explores several channels through which HIT adoption may affect the quality and quantity of care provided. First, EMR may reduce the effort cost to the physician of prescribing an extensive medical workup, which may increase the intensity of provided treatment. Second, EMR may improve communication across providers, which may in turn increase reliance on specialists and reduce redundant testing. Last, CDS may reduce medical errors and improve routine care by providing timely reminders to physicians. The net impact of these three channels on total medical expenditures, health outcomes, and quality of care is ambiguous.

I perform a detailed empirical analysis of the the impact of hospital HIT investment, using Medicare claims data. HIT is associated with 1.3 percent higher medical expenditures, with the 95% confidence interval ranging from −0.03 to 2.6 percent. Other results find that length of stay and number of physicians consulted do not change significantly after adoption. Despite the cost increases, HIT is associated with very modest reductions in patient mortality of 0.03 percentage points [95 percent confidence interval: −0.36 to 0.30 percentage points]. Further, there are no significant improvements in the complication rate, adverse drug events or readmission rate, after HIT adoption.

The results fail to measure a social benefit to HIT adoption over this period, although it should be noted that the finding is local both to the basic types of software systems commonly implemented over the study period, from 1998-2005, and the organizational structure of adopting hospitals. I will discuss these limitations further in the penultimate section of the paper.

These findings are estimated in a 20 percent sample of Medicare claims from 1998-2005; the sample includes 2.5 million inpatient admissions at 3880 hospitals. The claims data allows detailed tracking of patients' health outcomes, services rendered, and medical expenditures. HIT adoption is measured at the hospital level from the Health Information and Management Systems Survey (HIMSS).

A fixed effects econometric model exploits within-hospital across-time variation in HIT adoption status to estimate the effects of adoption. The multi-year panel data along with variation in the timing of HIT adoption allows the inclusion of rich controls for time trends beyond those used in conventional differencein-differences analysis; in particular, I control for state-year fixed effects, adopter-specific time trends, and differential trends that vary according to a hospital's baseline characteristics. I analyze potential threats to validity, testing for simultaneous changes in other hospital investments and probing the robustness of the results to any changes in patient sorting across hospitals.

Buntin et al. (2011) provide a review of recent literature on health IT, finding in a meta-analysis that 92% of studies suggested positive overall benefit to health IT. My analysis has several advantages over previous research. First, it estimates the impact of HIT over a broad, national sample of hospitals, rather than presenting a case study of a single institution or HMO (cf. Bates et al. 1999; Demakis et al. 2000; Evans et al. 1994; Javitt et al.). Second, it uses panel data to implement a difference-in-differences strategy, instead of relying on cross-sectional evidence (cf. DesRoches et al. 2010, Himmelstein et al. 2010).

My paper builds upon and complements the recent work on HIT with panel data by Miller and Tucker (2011), McCullough et al. (2011) and Furukawa et al. (2010). An advantage of my analysis is that it brings together a large set of outcome variables including medical expenditures and quality of care measures in addition to mortality rates, allowing a rich analysis of adoption costs and benefits; to my knowledge, it is the first large scale analysis of the impact of HIT on billing expenditures. Lastly, I implement a robust empirical strategy that controls for a rich set of state-by-year fixed effects and differential time trends that vary by hospital characteristics, rather than imposing uniform time trends across hospitals. This more flexible approach is particularly important for identifying the impact of HIT adoption on medical expenditures, as described in more detail in Section 3.1.

The paper proceeds as follows. Section 2 describes the data in more detail and discusses the HIT adoption decision. Section 3 presents the empirical strategy and results. Section 4 analyzes the policy implications and interpretation of these findings. The final section summarizes the results and concludes.

1 Data and Descriptive Statistics

1.1 Data sources and sample construction

I study the impact of HIT on the costs and quality of care between 1998-2005, using data from three sources: Medicare Claims Data from the Center for Medicare and Medicaid Studies, the Health Information and Management Systems Survey (HIMSS) conducted by the Dorenfest Institute, and the American Hospital Association Annual Survey.

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The HIMSS tracks HIT adoption at hospitals across the country; it includes questions about a wide variety of HIT functionalities and the timing of technology adoption. The annual survey includes 90 percent of non-profit, 90 percent of for-profit, and 50 percent of government-owned (non-federal) hospitals. It excludes hospitals with fewer than 100 beds. I construct an indicator variable of HIT adoption which equals one if the hospital has contracted either CDS or EMR.[1] As reported in Table 1, panel A, 54 percent of hospitals have contracted at least one of these two technologies by 1998, and an additional 23 percent of hospitals contract HIT for the first time during the study period.

The HIMSS data is, to my knowledge, the only broad panel data on HIT adoption over this period. A shortcoming of the data is that although it differentiates the adoption of many different software types, it does not record information on the quality of the HIT systems or the precise functionalities they include. I turn to the 2008 survey conducted by the American Hospital Association, reported by Jha et al. (2009a; 2009b), to understand which specific capabilities are likely to be included in the HIT installations I observe. This smaller survey covers 2370 hospitals, as compared to the 3880 hospitals included in the broader HIMSS data, and provides a snapshot of HIT installations in the 2008 survey year, a few years after the end of my study period in 2005.

Jha et al. (2009b) report that the four most common components of EMR are demographic characteristics (fully implemented in one or more unit at 89 percent of surveyed hospitals), medication lists (68 percent), discharge summaries (66), and list of current medical conditions (48.5); these four functionalities are likely to be features of the EMR systems I observe.

The most common features of CDS are drug allergy alerts (fully implemented in at least one unit at 68 percent of surveyed hospitals) and drug-drug interaction alerts. Roughly half of the CDS systems includes clinical guidelines and reminders, such as reminders to prescribe beta blockers after a myocardial infarction (30 percent) or provide pneumonia vaccines (38).

I link the HIT adoption survey to data on all Part A and Part B Medicare claims for a 20 percent sample of patients from 1998-2005. The Medicare claims data allows me to construct measures of patient health, medical expenditures, and the quality of hospital care. Because HIT adoption is observed at the hospital-level, I cannot observe which outpatient care providers are linked to an interoperable HIT system. For this reason, my analysis focuses on patients receiving inpatient care.

The sample includes patients admitted to a hospital with a primary diagnosis of acute myocardial infarction, stroke, hip fracture, lung cancer, colon cancer, gastrointestinal hemorrhage, or pneumonia. This set of diseases was chosen following previous work such as Baiker and Chandra (2004a) because hospitalization for these conditions is likely to be a good proxy for disease incidence. I follow all inpatient and outpatient Medicare claims for these patients for one year following their first in-sample hospital admission.

[1]In theory, CDS and EMR may have differential effects on the studied outcome variable; however, in practice, I do not find any evidence of significant differences between the effects of these two technologies. As a result, I combine them into a single indicator for HIT adoption.

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If HIT has heterogeneous effects which depend on patient age, then a limitation of this analysis is that it only identifies effects on the elderly Medicare population. The benefit of using Medicare data is that it allows me to measure the effects of HIT on a broad range of relevant outcome variables, in a panel data setting. In addition, Medicare enrolled 15 percent of the US population and accounted for 20 percent of total health spending in 2007, fractions that are likely to grow as the population ages. Elderly patients are highly likely to have multiple medical problems, putting them at greater risk for the coordination failures and medical errors that HIT is specifically designed to prevent.

Lastly, the Medicare claims and HIMSS data are supplemented with annual American Hospital Association (AHA) survey data. The AHA survey allows me to measure several key hospital characteristics, including hospital investments in other diagnostic and therapeutic technologies, staffing levels, and total number of patient admissions.

Data are matched across these three sources using the hospital's Medicare provider number. HIT adoption status is observed for a sample of 3880 hospitals. I am able to match 90 percent of Medicare inpatient stays to the IT adoption status of the admitting hospital. There are a total of 2.5 million individuals in the inpatient sample.

1.2 Summary Statistics

Table 1 provides an overview of hospitals' 1998 baseline characteristics by their adoption status. Adopting hospitals are larger on average than non-adopters, with twice as many inpatient beds, and an average of 8300 annual admissions compared to 3300 admissions for non-adopters. Adopters are more likely to be academic hospitals, be designated as a trauma center, and have adopted PET, MRI, and CT scanners. New scanners and new HIT systems both require large fixed cost investments, which may be more profitable for larger hospitals.

Patient characteristics do not differ as dramatically across hospitals. Comparing columns (1) and (2), adopters serve a slightly younger and more racially diverse population. Consistent with the younger population, adopters have a 0.7 percentage point lower one-year mortality rate amongst in-sample patients, as reported in panel D. Total medical expenditures in the one year following an inpatient admission are 30 percent higher for patients at adopting hospitals. Adopting hospitals offer more intensive treatment in the pre-period along a number of margins, including longer hospital stays, and more physicians evaluating each patient.

The pre-period differences between adopters and non-adopters suggest that it will be important in the remaining analysis to control for baseline differences and allow for the possibility of differential trends across hospitals with different adoption statuses. In addition, I will show that my results are robust to omitting the set of non-adopting hospitals from the estimation sample. I will further discuss the strategies I use to account for this heterogeneity in Section 4.1.

Two striking characteristics of this population indicate that it is particularly well-suited to identifying the impact of HIT. First, these patients are quite ill, with a 10 percent mortality rate in the baseline year. Thus, improvements in health may well be expected to occur along

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the margin of one year mortality, making survival a reasonable indicator of health in this sample. Second, a patient in this sample sees over ten unique physicians on average during their admission and the year following. The large number of providers per patient suggests that there is significant scope for coordination failures within this population.

2 Empirical Estimation Strategy

To examine how HIT affects medical expenditures and patient health, I use a fixed effects regression model as follows:

$$Y_{ht} = \boldsymbol{\alpha}_h + \beta HIT_{ht} + \boldsymbol{\gamma_{st}} + \mathbf{X_{ht}}\delta + \mu \text{Adopter}_h Yr_t + \mathbf{Q_h} Yr_t \nu + \epsilon_{\mathbf{ht}} \quad (1)$$

Y_h is the outcome variable for a hospital *h* at time *t*. α_h are hospital fixed effects. HIT_{ht} is a binary variable equal to one if a hospital has contracted either a clinical decision support or an electronic medical records system in the current year or in an earlier year. γ_{st} is a vector of state-year interacted fixed effects.[2] X_{ht} is a vector of hospital and patient characteristics. I control for the hospital's investment in CT, MRI, and PET scans, as well as its status as a trauma hospital. Included patient characteristics are 1-year age bins, race, sex, and primary diagnosis. $Adopter_h$ is a dummy variable which equals one if the hospital has adopted HIT by the end of the study period in 2004; this variable is interacted with a linear time trend. Lastly, Q_h is a vector of hospital size dummy variables, indicating which quartile the hospital falls into according to number of inpatient admissions in the 1998 base year; these variables are also interacted with the time trend.

Observations are at the hospital-year level based on the annual average of each variable across all in-sample patients admitted to that hospital. Accordingly, observations are weighted by the number of in-sample patients. There are 27,317 observations in total. Standard errors are clustered at the hospital level.

This specification is analogous to a difference-in-differences framework. The key coefficient of interest is β, which indicates how the outcome variable changes after a hospital has adopted health information technology. I compare the outcome variable within an adopting hospital before and after HIT adoption, controlling for the estimated counterfactual time trend the hospital would have experienced, had it not adopted HIT. Included state-year fixed effects capture state-specific shocks and trends in medical practice patterns or unobserved characteristics of the patient population. Including unrestricted, differential trends by quartile of hospital size and the hospital's eventual adoption status allows for different types of hospitals to experience different trends.

Identification of equation 1 is based on the assumption that adoption of HIT is not coincident with other discontinuous changes in hospital ownership, provider quality, or unobserved patient characteristics that would affect the measured outcome variables. Hospitals of the same size quartile, same eventual adoption status, and in the same state

[2]In addition to including state-year fixed effects, I have also run every specification including county-year fixed effects, and the results do not change substantially. An F-test rejects the joint significance of the county-year fixed effects, after the inclusion of state-year effects, so county-year fixed effects are omitted from the specifications reported here.

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must be on parallel trends in the absence of HIT adoption, after controlling for observable changes in patient diagnoses and demographics.

To illustrate the importance of controlling for flexible time trends, I report additional results for my two main outcome variables—medical expenditures and mortality rates—that begin with a simple difference-in-differences specification and add controls. The simple difference-in-differences specification controls only for hospital fixed effects and (uniform) year fixed effects. From that baseline, I sequentially add: interacted state-year fixed effects; time-varying hospital controls and differential trends by quartile of hospital size; and differential pretrends by eventual IT adoption status. As we add controls, the estimated impact of HIT adoption on medical expenditures attenuates. I discuss these findings further in section 3.1.

One way to assess the success of these control variables for differential time trends is through the related set of graphical results. The main results are displayed in graphs based on regressions which include the same set of fixed effects and controls listed in Equation 1, but replace the key independent variable with a series of dummy variables indicating the year in normalized time. The coefficients on these normalized year dummy variables provide a year-by-year estimate of the treatment effect in event time. In the graphs, we can see that medical spending and mortality risk appear stable at adopting hospitals in the years prior to HIT adoption.

In addition to allowing an assessment of pre-trends, this series of graphs provides a nonparametric way of assessing how the outcome variable evolves after HIT adoption. The HIMSS survey data measures the year in which HIT was first contracted from the software vendor; installation and implementation may be rolled out gradually in the year or two following the initial contract. Thus, these figures are useful for assessing whether the full impact of HIT is not realized until a few years after adoption.

Each of these specifications remains vulnerable to the possibility that some unobserved characteristic of the hospital or its patients changed right at the time of HIT adoption, thus confounding the estimated treatment effects. I deal with this threat to validity in three ways. First, I directly control for observed patient and hospital characteristics that may be evolving at the time of HIT adoption. Second, in Section 3.4, I demonstrate that these observable characteristics are not changing discontinuously at the time of HIT adoption. However, both of these approaches are vulnerable to the possibility that *unobserved* patient characteristics are changing at the time of HIT adoption. To address potential changes in patient sorting, I have tested specifications that change the unit of observation from the hospital to the county to account for the possibility that patient sorting may be more severe across hospitals within a county, rather than across counties. I show that the conclusions do not change in the county-aggregated specifications.

My primary outcome variables are patient mortality and 1-year medical expenditures. In addition to these outcomes, I report results on a number of auxiliary measures, including length of stay, number of physicians seen, readmission rates, complication rates, and adverse drug events. To improve the power of my tests and reduce the rate of false positive results, I

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group these auxiliary outcome variables into two conceptual categories and create standardized effect measures across outcomes. The two domains are: intensity of treatment and quality of inpatient hospital care.

These groupings allow me to perform omnibus tests analyzing whether HIT is affecting treatment patterns in a particular direction within a domain. I report separate results for each outcome variable, as well as the aggregated standardized effect. I account for the cross-equation covariance structure of the error terms when estimating standard errors for each outcome within a domain. Standard errors remain clustered at the hospital level.

The standardized effect is constructed by combining the estimated coefficients across each outcome variable within a domain. In particular, the standardized effect equals:

$$\sum_{j \in J} \frac{1}{J} \frac{\beta_j}{\sigma_j}, i \in \{1, 2\} \quad (2)$$

where β_j is estimated by Equation 1 for outcome variable j. σ_j is the standard deviation of the outcome j amongst the hospitals that eventually adopt HIT, in the baseline year of 1998, prior to their adoption. Dividing by the standard deviation harmonizes the units across the diverse outcome variables. J is the total number of outcomes within a domain.

3 Empirical Results

3.1 Impact of HIT on Mortality and Expenditures

Table 2, panel A, reports the regression results on medical expenditures. Column (1) reports results from the simple difference-in-differences regression, controlling only for hospital fixed effects, year fixed effects and patient characteristics. Column (2) adds interacted state-year fixed effects. Column (3) adds time-varying controls for hospitals' technology investment as well as time trends that vary by quartile of hospital size. Column (4) gives the full preferred specification, adding a differential pre-trend amongst IT adopters, and matching the specification described above in Equation 1.

Looking across the columns, the estimated impact of HIT adoption on medical expenditures attenuates as I add controls for time trends, from 2.01% in the simple difference- in-differences specification to 1.29% in the fully controlled specification. I prefer the specification that includes the full set of differential time trends and interacted state-year fixed effects, since it mitigates bias from differential trends and isolates the impact of IT adoption from these potential confounding factors. According to the most conservative estimate reported in column (4), HIT is associated with initial increases in spending of 1.3 percent (p=5.6 percent), or about $570 per patient in sample. The 95 percent confidence interval suggests that there are no substantial decreases in expenditure, with the lower bound at a 0.03 percent decrease and the upper bound a 2.6 percent increase. I will further unpack the relationship between HIT adoption and medical expenditures in Section 3.2.1, analyzing which services drive the estimated increase in expenditure.

Figures 1A illustrates the relationship between HIT adoption and medical expenditures graphically. Figure 1A corresponds to the fully controlled specification described in

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Equation 1 and illustrates that after controlling for appropriate trends, spending is stable during the pre-period. The graph suggests that medical expenditures rise following HIT adoption, and that the full effect takes a few years to be realized, which is consistent with potential delays from the contract date to full implementation and usage of the software. Importantly, there is no evidence of reduced spending even four years following initial HIT adoption.

Results reported in Table 2, panel B, find no significant relationship between HIT adoption and 1-year patient mortality. Unlike the expenditure results, these findings on mortality do not substantively depend on the choice of regression specification. The corresponding graph, reported in Figure 1B, does not display evidence of differential pre-trends amongst HIT adopters. For consistency with the expenditure results, I focus the discussion that follows for all of the reported outcomes on the full regression specification as reported in column (4). However, it is only for the expenditure outcome variables that the inclusion of differential time trends leads to substantial changes in the estimated regression results.

The point estimate in Table 2, column (4) suggests that HIT is associated with a 0.03 percentage point reduction in the mortality rate. The 95 percent confidence interval on the mortality effect in Table 2, column (4), bounds an effect not larger in magnitude than a decrease of 4 deaths or increase of 3 deaths per 1000 patients, relative to a mean of 100 deaths per 1000. Figure 1B confirms the small, insignificant effect size, with the mortality rate in years 0 through 5 remaining very close to the baseline levels before HIT adoption.

The modest increases in medical expenditures coupled with the lack of significant improvement in the mortality rate could be evidence of either flat-of-thecurve medicine or HIT-driven improvements in billing capture. By reducing the effort cost of intensive treatment, HIT may encourage the provision of care, even if the medical returns to this additional care are low. The lack of a mortality response in tandem with expenditure increase is consistent with evidence from many recent studies (Murphy and Topel 2003; Baiker and Chandra 2004b). Alternatively, HIT systems may assist in “upcoding” patients to higher reimbursing billing codes, without changing medical behavior. This behavior would also drive increased expenditures with no commensurate improvement in mortality rates.

To further investigate the potential impact of HIT, I analyze how HIT may change the intensity of treatment and quality of care provided. If HIT is to improve health, it may do so through a number of channels previously outlined: reducing adverse drug events, medical complications, and readmissions. If HIT is associated with cost savings, we may observe shorter lengths of stay and less expenditure on imaging. Testing these specific channels will illuminate the cost–benefit tradeoffs by providing additional evidence of the impact along both of these margins.

3.2 Impact of HIT on the Intensity and Efficiency of Hospital Care

3.2.1 Medical Expenditures—The increase in medical expenditures reported in Table 2 could be driven by several factors: inpatient hospital spending, professional services, procedures, emergency care, drugs, or testing and imaging. I investigate each of these sources of spending in turn; findiings are reported in Table 3.

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First, analyzing changes in spending on inpatient hospital stays, I decompose this into three parts: spending on the initial stay, number of inpatient stays within one year, and average spending on subsequent stays. I estimate that spending on the initial inpatient stay increases by 1.3%, significant at the 10 percent level (95% CI: −0.2% to 2.8%). There is no evidence of change in the total number of hospital stays within one year of the initial admission, with a small, insignificant estimated coefficient. The 95% confidence interval on number of stays bounds the effect between 0.004 fewer and 0.02 more stays, from a mean of 2 stays. Compared to the change in spending on the initial visit, I find HIT is associated with more modest, insignificant increases in spending on subsequent hospital visits of 0.7%; some attenuation would be expected in this coefficient since patients are not always readmitted to the same hospital so some subsequent stays may be at non-adopting hospitals.

Moving to physician and outpatient expenses billed through Medicare Part B, I rely on BETOS and type of service codes to group claims from the carrier and outpatient files, respectively. For these results, I report evidence on average spending measures rather than log spending, since not all patients have spending in each category. (Results on log spending measures for patients with nonzero spending are consistent with these findings.) I find no evidence of significant changes in spending on emergency services, procedures, or testing and imaging. Notably, I find that spending on pharmaceuticals drops by $92 dollars per patient, significant at the 5% level; the measured increase in aggregate spending masked the decline within this category. Note that this measure of pharmaceutical spending only includes drugs covered through Medicare Part B, which is limited to drugs typically administered in a doctor's office or outpatient hospital setting.

Together, these findings indicate that the increase in total spending is driven primarily by growth in spending on hospital stays. Since the measure of HIT adoption applied here captures IT usage at the hospital level, it is not surprising that we find the largest impact on hospital care. Given the capitation structure of Medicare inpatient hospital payments, part of the increase may be due to IT-driven improvements in coding of patient conditions and comorbidities to capture higher payments for each patient.

In results unreported in tables, I directly investigate whether HIT adoption is associated with greater "upcoding", i.e. assigning patients to diagnosis related groups (DRGs) associated with greater complexity. I study patients assigned to DRG pairs where both DRGs indicate the same underlying condition but one code stipulates a higher complexity case due to the patient's "comorbidities or complications". On average, 89% of patients in one of these pairs are assigned to the higher complexity DRG. A regression was run that mirrored my preferred specification in equation 1, but now restricting only to the 47% of patients in one of these paired DRGs and controlling for DRG pair by year interacted fixed effects.

I find a 0.36 percentage point increase in the probability of being coded with the more complex DRG within a pair after HIT adoption; the 95% confidence interval runs from a 0.03 percentage point decline to a 0.76 percentage point increase. This finding is consistent with modest increases in upcoding, although this type of upcoding explains only a 0.19% increase in expenditures.[3] While I cannot rule out the possibility that a more complex pattern of coding changes contributes to the observed 1.29% increase in expenditures, this type of upcoding to more complex DRGs explains only about 7% of the total expenditure change.

3.2.2 Length of Stay and Reliance on Specialists—

I now investigate the relationship between HIT and intensity of treatment by analyzing the impact on length of stay and reliance on medical specialists. If HIT makes it easier for a physician to order a more extensive workup, we may expect longer hospital stays following adoption. Results on length of stay are reported in column (1) of Table 4, panel A. HIT adoption is not associated with any substantial change in length of stay, with the 95 percent confidence interval bounding the effect between 1 hour shorter stay and 1 hour longer stay per patient, from a mean of 7 days per patient.

If HIT made it easier for physicians to communicate with each other by allowing them to share notes electronically, we might expect that more specialists would be consulted after IT adoption. Yet, I find no evidence of change in the total number of physicians seen within 1 year of admission as reported in column (2) of Table 4, panel A. The 95% confidence interval bounds the effect between 0.6% decrease and a 1.3% increase in the number of physicians seen by each patient. This is consistent with the finding reported in Table 3 of no significant increase in billing for professional services.

Turning our attention to the standardized composite effect reported in Table 4, column (4), I find no significant relationship between HIT adoption and this measure of treatment intensity. This result is displayed graphically in Figure 2A. The 95 percent confidence interval around the estimate is bounded between a 0.01 standard deviation decline and 0.02 standard deviation increase in the intensity of treatment, confirming that HIT adoption is not associated with economically substantial or statistically significant cost reductions and efficiency improvements, over the study period.

3.3 Impact of HIT on Hospital Quality

In this section, I analyze the impact of HIT on three measures of the quality of inpatient hospital care: 30-day readmission rate, complication rate, and adverse drug events. The results are reported in Table 4, panel B. Consistent with the null results on mortality, I find no impact of HIT on the 30-day readmission rate. A high readmission rate may indicate inadequate treatment of a patient's needs during their admission, and as such, poor quality of care. Incorrect prescriptions for the patient's home regimen and inadequate followup can also drive rising readmission rates. By improving the quality of inpatient care and making it easier to track the patient's medication list and construct an appropriate home regimen, HIT could reduce readmission rates. The lower bound on the 95 percent confidence interval suggests any reduction in readmission rate is not greater than 1 fewer readmission per 330 patients, from a mean of 28 readmissions per 330.

[3]Medicare reimbursement is calculated as a multiplier of the weight assigned to each DRG. I replace the natural log of DRG weight as the dependent variable in a regression that matches the specification used to test for upcoding, restricting to the 47% of patients in a paired DRG. Due to the inclusion of DRG pair by year fixed effects, this regression will test only for increases in billed DRG weight due to within-pair switching to the higher complexity DRG. I find that HIT adoption is associated with 0.15% increase in DRG weight, with the 95% confidence interval running from a 0.04% decline to a 0.41% increase.

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I similarly find no association between HIT adoption and complication rates, as reported in columns (2) of Table 4, panel B. Following Hougland et al. (2009), I measure the frequency of medical complications based on ICD-9 codes reported by the physician and hospital, which includes complications such as infection, hemorrhage due to procedure, or abnormal reaction to surgery. The 95 percent confidence interval on medical complication rates bounds the estimate very close to zero: between a 0.4 percentage point reduction and 0.04 percentage point increase, from a mean of 6.5 percentage points.

Next, I analyze rates of adverse drug events. Rates of adverse drug events are also constructed on the basis of provider-reported ICD-9 codes, and include failures in dosage, accidental poisoning by drugs, or complications caused by the use of a medication (Hougland et al. 2009). This outcome is most directly linked to the common features of the HIT software—medication lists, drug-drug interaction reminders, and drug allergy flags are major components of popular HIT systems. In column (3), I estimate a slight 0.14 percentage point increase in adverse drug events associated with HIT adoption, significant at the 10 percent level; this is equivalent to a 9 percent increase in the rate of adverse drug events. The effect is only marginally significant, but suggests that HIT adoption is not associated with reduced risk of pharmaceutical mismanagement.

Lastly, the standardized composite effect summarizes the findings across these three measures and finds no evidence of improvements in the quality of inpatient care. The composite effect is bounded between a −0.03 and 0.02 standard deviation change in the quality of care. Indeed, Figure 2B illustrates the flat path of the quality of care composite after HIT adoption.

3.4 Threats to Validity and Extensions

3.4.1 HIT Adoption and Patient Composition—The results suggest that HIT adoption is not associated with improvements in patient health, care quality, nor reductions in medical expenditures over the study period. One potential explanation for these findings is that after HIT adoption, the patient population being treated at adopting hospitals becomes more complexly or acutely ill, along dimensions not fully captured by the included patient demographic and diagnosis controls.

To address the concern of patient sorting, I test directly for compositional changes in the patient population after HIT adoption. Using patient characteristics as the outcome variables of interest, I run a series of regressions analogous to the specifications in Equations 1. For these results I omit patient and hospital characteristic controls from the right-hand side.

Reported in Table 5 panel A are tests of the joint significance of the coefficients estimating the impact of HIT adoption on demographics and case mix, respectively, in a seemingly unrelated regression framework. I cannot reject the null hypothesis that there is no change in patient demographics (patient age, race, and sex) after HIT adoption; the p-value is 0.500. Similarly, I find no evidence of changes to a hospital's case-mix after HIT adoption; the p-value of this test is 0.967, The evidence presented in this section suggests that changes in patient composition are unlikely to be driving the earlier null results on health outcomes and positive findings on expenditures and imaging frequency, although I cannot rule out the possibility that patient selection is changing along unobservable dimensions at the time of adoption.

3.4.2 HIT Adoption and Other Hospital Investments—A second factor that may potentially confound estimates of the effect of HIT is that hospitals that choose to invest in HIT may be making other changes to their organizations. If hospitals were simultaneously investing in new imaging technology, for example, then these changes could be driving the estimated increases in spending. In Table 5 panel B, I analyze whether hospitals adopting HIT are also purchasing other costly medical technologies.

I construct an index of investment in medical technology, which is the sum of three indicator variables for whether the hospital has adopted a positron emission tomography (PET) scanner, magnetic resonance imaging (MRI) scanner, and computed tomography (CT) scanner. Although HIT adopters are more likely to have each of these three technologies in the baseline year, investment in these technologies is uncorrelated with the timing of the HIT adoption decision as reported in column (1).

Column (2) of Table 5 panel B tests whether HIT adoption is related to a hospital's status as a trauma center. To obtain designation as a trauma center, a hospital must have the resources to evaluate and stabilize severely injured patients, including the capability for emergency resuscitation, surgery, and intensive care. HIT adopters are 3 percentage points less likely to be designated trauma centers after adoption, significant at the 5 percent level. One explanation is that the large investments made in HIT adoption crowd out investment in becoming a designated trauma center. Trauma centers admit more critically ill patients, and thus may have worse health outcomes than other hospitals. The fact that HIT adopters are less likely to become trauma centers suggests that adopters may have a healthier patient population. This will bias the results towards finding a positive impact of HIT on health. To mitigate bias from this confounding factor, I directly control for trauma hospital status in all of the regression specifications reported in earlier tables, although adding this control does not materially change the results.

Lastly, I study whether hospitals adjust staffing inputs around the time of HIT adoption. The available measure of staffing includes nursing and other support, facilities, and managerial staff, including IT personnel. In panel C, column (1), I find that HIT adoption is associated with modest, though statistically insignificant, 1.5 percent increases in total non-physician staff. Increased demand for IT support may account for some of this rise. Column (2) reports that nursing staff increases by 1.1 percent after HIT adoption, but the change is also not statistically distinguishable from zero. This finding suggests that the measured increase in total staffing is not driven solely by IT staff. Furthermore, there is no evidence that HIT adoption is associated with reductions in nursing staff, despite the fact that some of the functions automated by HIT systems may replace bookkeeping and report generating work previously done by nurses.

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3.4.3 Alternative definitions of HIT adoption—Table 6 tests whether other HIT functionalities besides electronic medical records (EMR) and clinical decision support (CDS) may have greater returns. In panel A, I analyze the impact of computerized physician order entry systems (CPOE), which may allow a doctor to electronically order tests or medications for a hospital patient. Computerized order entry may reduce medical error and expenditures by ensuring timely electronic transfer of clearly typed instructions, providing recommendations for the dosing of common drugs, and reminding the prescribing physician of the hospital formulary.

The regressions match the specification described in Equation 1, changing the key dependent variable of interest to measure adoption of CPOE rather than EMR or CDS adoption. Results echo those reported earlier for EMR and CDS adoption. In particular, CPOE adoption is associated with a 3% increase in medical expenditures (significant at the 1% level), but no significant changes in patient mortality, intensity of care (length of stay, number of physicians), or quality of care (readmission rates, medical complications, adverse drug events).

Table 6, panel B reports the impact of adopting three key ancillary HIT systems in tandem: computerized physician order entry, laboratory information systems, and radiology information systems. Laboratory and radiology information systems are designed to make the results of patients' lab tests, radiology images, and radiology reports available electronically to physicians. Again, the specification matches Equation 1, but here a hospital must have adopted all three ancillary HIT systems in order to be coded as an adopter. Again, I find evidence of increases in medical expenditures by 1.6% (significant at the 5% level), but no evidence of changes in patient mortality, intensity or quality of care.

3.4.4 Robustness Tests—Further robustness tests are reported in online appendix tables A1 and A2. In Table A1, I aggregate the unit of observation from the hospital to the county level. If there is a greater scope for sorting across hospitals within a county, but little scope for sorting across counties, then these results will mitigate bias due to unobserved patient sorting. The results are very similar to those reported earlier. Because aggregating to the county reduces precision without changing the overall findings, I prefer the hospital-level analysis for my main results.

Also reported in appendix A1, I test the concern that heterogeneity across adopting and non-adopting hospitals makes non-adopting hospitals a poor control group. Omitting the non-adopters from the regressions, I can estimate the impact of HIT using only adopting hospitals to estimate the time trends and impact of control variables. The results are again extremely close to the baseline regression results.

Appendix A2 explores potential heterogeneous returns to HIT adoption. In Table A2 panel A, I show that larger hospitals which may have greater ex ante coordination challenges do not experience larger returns to HIT adoption than smaller hospitals. In Table A2 panel B, regressions are reported that test whether hospitals adopting both EMR and CDS as well as a clinical data repository experience higher returns than hospitals that have adopted only one of those components. A clinical data repository integrates all electronic patient information

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into a single interface, and is thus thought to make the decision support and electronic record systems easier to use. The results find no evidence of higher returns to more comprehensive HIT systems.

4 Interpretation and Policy Implications

On the whole, my results suggest that hospital HIT installations between 1998 and 2005 made little progress towards improving the quality and efficiency of the American healthcare system. HIT adoption was not associated with better health outcomes or reduced costs. This runs contrary to the expectations of many policymakers and the optimism of much of the academic literature.

One potential explanation for the low observed returns is that physicians have little incentive within most organizations and current reimbursement structures to reduce treatment intensity. Even if HIT could be a useful tool for reducing billing costs or improving quality, there is no a priori reason to believe that physicians will use it to do so within the current context.

Bresnahan, Brynjolfsson, and Hitt (2002) find that it is often the combination of IT adoption and complementary organizational and technical innovation that leads to productivity gains. Cutler (2010) applies this argument to the healthcare sector, arguing that coupling information technology with organizational change may tremendously reduce the existing inefficiencies. Even if HIT could be a useful tool for reducing costs and raising the quality of care in a different institutional context, these returns may not be realized without changes to the current organizational structures and incentives facing care providers.

A second explanation for this finding is that HIT systems will evolve and improve, so future gains to adoption may greatly exceed the impact estimated here. The effects of HIT that I measure in this paper are local to the types of HIT commonly adopted over the study period. Within this data, I find no evidence that more comprehensive HIT systems are associated with significantly more favorable outcomes than basic IT installations. However, if new systems differ substantially from those currently offered, or if there are large positive synergies to adopting many ancillary components of an HIT system, then the results estimated here will not capture the full returns.

A third possibility is that users take time to learn how to apply the software effectively to their own work. This is a popular explanation for the productivity paradox of the 1980s and early 1990s, about which Robert Solow observed, “We see the computers everywhere but in the productivity statistics.” David (1990) argues that information technology may require a long time scale to realize substantial returns, following the historical pattern of the productivity gains of the dynamo. This hypothesis is difficult to test empirically, both because it requires a long data series, and because such a long-delayed relationship may be difficult to distinguish from other trending factors. Nevertheless, the preceding analysis cannot rule out this possibility.

Within the limited window of the 8-year study period, the gains to HIT adoption do not appear to change substantially in the third, fourth, and fifth years after adoption. Indicators

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of patient mortality, readmissions, complications, and errors do not trend significantly downward several years after HIT adoption, as can be seen in Figures 1 and 2. There are no signs of cost savings, even five years after initial adoption. The results do not suggest substantially higher returns to adoption even after physicians and nurses have had a few years to adjust to the new software systems.

A limitation of this analysis is that I do not test how HIT affects hospital operating costs; it may, for example, reduce bookkeeping costs or increase the number of outpatient clinic patients a physician can evaluate in a fixed amount of time. Lacking data on hospital's cost structures, this paper focused on measuring the health, quality of care, and medical billing impact. Recent work by Dranove et al. (2012) investigated the impact of EMR adoption on hospital operating costs; they find adoption is associated with slightly higher average operating costs, but that for hospitals located in areas with a high concentration IT-intensive industries, cost savings are realized three years following HIT adoption.

The evidence presented here suggests that there is little social benefit to HIT adoption in the inpatient hospital setting over the study period. The argument for public subsidies of HIT adoption then hinges on the expectation that returns to HIT adoption will be higher in the future, perhaps in part due to innovation induced by the regulatory requirements of the HITECH Act. Meeting the "meaningful use" requirements to receive federal subsidies will require significant improvements in HIT systems, and studying the impact of these improvements will be an important avenue for future research.

A complementary research agenda would investigate whether particular organizational or reimbursement structures encourage higher-return adoption of HIT. As the healthcare industry continues to experiment with accountable care organizations and other alternative incentive structures, studying the potential complementarities between payment reform and IT adoption will be of particular importance.

5 Conclusion

This study has analyzed the effects of health information technology adoption on the quality and intensity of medical treatment. The basis of the empirical analysis is a comparison of adopting hospitals before and after they first contract a basic HIT system. The impact of HIT adoption on Medicare patients receiving inpatient hospital care is measured using claims data from 1998-2005.

Medical expenditures increase by approximately 1.3 percent after HIT adoption, in particular due to higher charges for inpatient hospital stays. The cost increases are imprecisely measured, although we see no evidence of savings even four years after HIT adoption. Patient length of stay and the number of physicians each patient sees also do not change following HIT adoption. Furthermore, the quality of hospital care, as measured by the mortality rate, readmissions, adverse drug events, and complications, is unaffected HIT investment. These results are robust to alternative specifications, including aggregating to the county level to mitigate potential bias due to patient selection, and omitting hospitals that never adopt HIT from the estimation sample. Overall, I find that HIT adoption is not

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associated with either reduced health spending or improved health outcomes over the study period. The evidence suggests that further research should be pursued into the conditions that might allow HIT to realize positive returns.

Acknowledgments

I would like to thank David Autor, Amy Finkelstein, and Michael Greenstone for invaluable guidance throughout this project. I gratefully acknowledge David Cutler and Frank Levy for their very helpful comments and suggestions. I thank Jason Abaluck, Joshua Angrist, Joshua Aronson, Robert Gibbons, Jonathan Gruber, Danielle Li, Amanda Pallais, Catherine Tucker, Heidi Williams, and seminar participants at Boston University SM, Cornell PAM, HBS, MIT, Northwestern Kellogg, RAND Institute, UC-Irvine Merage, UCLA School of Public Affairs, University of Illinois College of Business, University of Michigan Ross, US Department of Health and Human Services, Wharton, and Yale SOM for their comments. I am also grateful to Mohan Ramanujan and Jean Roth for their assistance in obtaining and managing the data. Financial support was provided by the NSF Graduate Research Fellowship and the NIA Grant Number T32-AG000186 to the NBER.

Appendix

Appendix: Table A1

Robustness tests

	Log(medical expenditures		**Patient mortality**		**Standardized intensity composite**		**Standardized inpatient quality composite**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
			A. Aggregate Unit of Observation to County Level					
HIT adoption	0.01004	0.00862	0.00009	−0.00011	0.01866	−0.00788	−0.01259	−0.00800
	(0.01040)	(0.01314)	(0.00240)	(0.00282)	(0.01453)	(0.01754)	(0.01830)	(0.02115)
Post adoption trend		0.00099		0.00013		0.01447		−0.00250
		(0.00403)		(0.00118)		(0.00384)		(0.00455)
3-year effect		0.01159		0.00030		0.03552		−0.01551
		(0.01069)		(0.00315)		(0.01421)		(0.01835)
Mean dep. var.	$44,385	$44,385	0.0993	0.0993				
				B. Exclude Never-Adopting Hospitals				
HIT adoption	0.01309*	0.01779**	−0.00025	0.00076	0.00703	0.00358	−0.00461	0.00072
	(0.00668)	(0.00827)	(0.00170)	(0.00194)	(0.00845)	(0.01109)	(0.01450)	(0.01787)
Post adoption trend		−0.00323		−0.000692		0.00239		−0.00368
		(0.00254)		(0.00074)		(0.00368)		(0.00604)
3-year effect		0.00811		−0.00132		0.01074		−0.01033
		(0.00700)		(0.00212)		(0.00890)		(0.01622)
Mean dep. var.	$44,385	$44,385	0.0993	0.0993				

Notes: Panels A & B: The entries report the coefficients and standard errors. The dependent variable is noted in the column labels. Each regression controls for county fixed effects, state-year fixed effects, and a differential time trend amongst adopting counties. Additional controls include: patient age (in 1-year bins), sex, race, primary diagnosis. hospital's investment in CT, MRI, and PET scans, and trauma hospital status. Regressions are weighted by the number of patient observations that make up each observation.

Panel A: An observation is a county-year, 1998-2004. There are 14,279 observations in total. Standard errors are clustered by county.

Panel B: An observation is a hospital-year, 1998-2004. There are 21,068 observations in total. Standard errors are clustered by hospital. In addition to controls listed above, regressions include linear time trends that vary by quartile of hospital size.

*** denotes significance at 1 percent level;

** denotes significance at 5 percent level;

* denotes significance at 10 percent level.

Appendix: Table A2

Heterogeneous returns to HIT adoption

	Log(Medical expenditures)		Patient mortality	
	A. Hospital Size: Top vs. Bottom Quartile			
	Large hospital	Small hospital	Large hospital	Small hospital
HIT adoption	0.01452	.02888***	−0.00164	−0.00771
	(0.01576)	(0.00389)	(0.00375)	(0.00173)
p-value		0.376		0.141
	B. Type of HIT System: Basic vs. Comprehensive			
	Basic HIT system	Comprehensive HIT system	Basic HIT system	Comprehensive HIT system
HIT adoption	.01407**	0.00431	−0.00043	0.00055
	(0.00680)	(0.00828)	(0.00171)	(0.00215)
p-value		0.094		0.510

Notes: Panels A and B: All regressions include HIT Adoption as the explanatory variable of interest. Each regression controls for hospital fixed effects, state-year fixed effects, and a differential time trend amongst adopting hospitals. Additional controls include: patient age (in 1-year bins), sex, race, primary diagnosis, hospital's investment in CT, MRI, and PET scans, and trauma hospital status. The "p-value" row reports the p-value from a test of equality of the two coefficients listed in the preceding columns. Regressions are weighted by the number of patient observations that make up the hospital-year observation.

Panel A: The entries report results from 4 separate regressions, where the dependent variable is noted in the column header at the top. Regressions are run separately for the sub-sample of lowest size quartile hospitals (5630 observations), and the sub-sample of highest size quartile hospitals (6784 observations).

Panel B: The entries report results from 2 separate regressions, where the dependent variable is noted in the column header at the top. In addition to the controls listed above, these regressions include time trends that vary by quartile of hospital size. There are 27,317 observations.

*** denotes significance at 1 percent level;

** denotes significance at 5 percent level;

* denotes significance at 10 percent level.

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Highlights

- I analyze the impact of health information technology adoption (HIT) at hospitals
- Analysis uses Medicare claims data from 1998-2005
- I estimate the effects of HIT by exploiting time variation in hospitals' adoption
- HIT is associated with a 1.3% increase charges billed for Medicare patients
- HIT has little impact on mortality, adverse drug events, and readmission rates

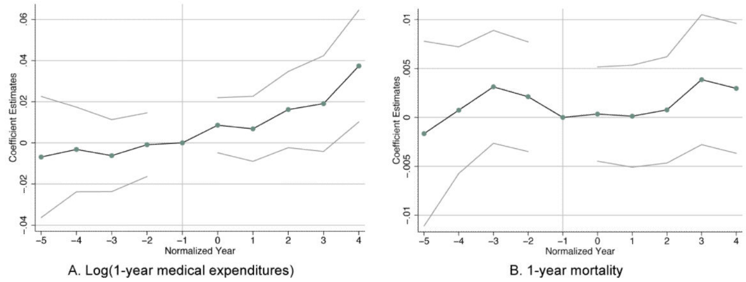

Figure 1.

Impact of HIT on Expenditures and Mortality

Notes: Each panel of this figure plots regression coefficients and 95 percent confidence intervals from a single regression where the dependent variable is indicated in the caption. The regression includes a series of explanatory dummy variables indicating the year relative to initial HIT adoption for hospitals that change their adoption status over the study period. Adoption occurred in year 0. The outcome variable in panel A is total medical expenditures over 1 year following initial admission, and the outcome in panel B is 1-year mortality. Regressions control for or hospital fixed effects, state-year fixed effects, a differential time tread amongst HIT adopting hospitals, time trends that vary by quartile of hospital size, trauma hospital status, hospital investment in CT, PET and MRI scanners, as well as patient age (in 1-year bins), sex, race, and primary diagnosis code. An observation is a hospital-year, 1998-2004. There are 27,317 observations in total. Regressions are weighted by number of patients, and standard errors are clustered by hospital.

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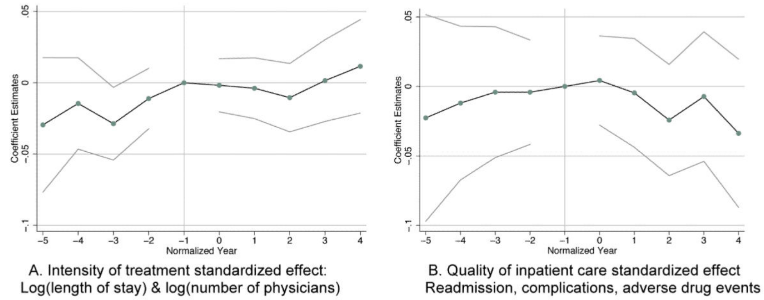

Figure 2.

Impact of HIT on Intensity Quality of Care

Note: Each panel plots regression coefficients and 95 percent confidence intervals (in grey) from a single regression. The regression includes a series of explanatory dummy variables indicating the year relative to initial HIT adoption. Adoption occurred in year 0. There are 27,317 observations. See noted to Figure 1 for further details.

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Table 1

Summary Statistics, 1998 Baseline

	HIT Switchers (1)	Never HIT (2)	Always HIT (3)
A. Sample Size			
No. of hospitals	882	915	2086
No. of sampled patients per hospital	79	35	85
B. Hospital Characteristics			
No. of beds	209	101	223
Total admissions	8298	3300	9078
Total Medicare admissions	3187	1391	3487
FTEs	953	418	1075
Trauma hospital	0.300	0.235	0.322
Academic hospital	0.229	0.07	0.263
PET scanner	0.087	0.032	0.093
MRI machine	0.648	0.356	0.655
CT scanner	0.949	0.801	0.930
C. Sample Patient Characteristics			
Minority fraction	0.136	0.116	0.133
Age	77.0	77.8	76.6
D. Patient Outcomes			
Medical expenditures: 1 year	$44,385	$34,052	$44,450
Mortality rate: 1 year	0.0993	0.106	0.099
E. Intensity of Treatment			
Length of stay	6.9	6.6	7.0
Number of physicians: 1 year	13.3	10.5	13.4
F. Hospital Quality			
Medical complication	0.065	0.044	0.066
Medication error	0.016	0.019	0.018
Readmission	0.0843	0.082	0.085

Notes: All summary statistics are calculated on an annual basis for the 1998 base year.

A hospital is considered an “HIT Switcher” if it adopts HIT between 1999-2004, and thus can be used to identify the effects of HIT adoption in the subsequent regressions. A hospital is in the “Always HIT” category if HIT was adopted prior to 1999. Hospitals in the “Never HIT” category have not adopted by the end of the study period. HIT is defined here as the adoption of at least one of the following technologies: clinical decision support or electronic medical records.

Hospital characteristics are from the AHA survey; HIT adoption is from the Health Information Management Systems Survey; all other variables are from the Medicare claims data.

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Table 2

Effect of HIT adoption on health and total expenditures

	(1)	(2)	(3)	(4)
	A. Log(medical expenditures)			
HIT adoption	0.0201**	0.0173**	0.0156**	0.0129*
	(0.0077)	(0.0067)	(0.0067)	(0.0067)
Mean dependent variable	$44,385	$44,385	$44,385	$44,385
	B. Patient mortality			
HIT adoption	−0.0001	−0.0004	−0.0004	−0.0003
	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Mean dependent variable	0.0993	0.0993	0.0993	0.0993
State*Year Fixed Effects?	No	Yes	Yes	Yes
Hospital trends & controls?	No	No	Yes	Yes
Differential pre-trend?	No	No	No	Yes

Notes: The entries report the coefficients and standard errors from 8 separate regressions, where the dependent variable is Log(1-year medical expenditures) in panel A, and 1-year patient mortality in panel B. In each regression, HIT adoption is the key explanatory variable of interest.

Column 1 reports results from a simple difference-in-differences specification, and each subsequent column augments this baseline specification with additional control variables. All regressions control for hospital fixed effects, year fixed effects, patient age (in 1-year bins), sex, race, and primary diagnosis. Column 2 regressions add state-year interacted fixed effects. Column 3 regressions add differential trends by quartile of hospital size, as well as controls for hospitals' investment in CT, MRI, and PET scans, and trauma hospital status. Column 4 regressions control for a differential trend amongst HIT-adopting hospitals.

An observation is a hospital-year, 1998-2004. There are 27,317 observations. Regressions are weighted by the number of patients and standard errors are clustered by hospital.

*** denotes significance at 1 percent level

** at 5 percent level

* at 10 percent level.

Hospital characteristics are from the AHA survey; HIT adoption is from the Health Information Management Systems Survey; all other variables are from the Medicare claims data.

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Table 3

Effect of HIT Adoption on Components of Medical Expenditures

	(1)	(2)	(3)	(4)
	A. Medicare Part A Inpatient Expenditures & Part B Emergency Care Expenditure			
	Log(expenditure on first inpatient stay)	Number of inpatient stays	Log(expenditure on subsequent stays)	Emergency Room ($)
HIT adoption	0.0133*	0.0078	0.0074	19.88
	(0.00763)	(0.00610)	(0.00680)	(17.32)
Mean dep. var.	$15,191	2.009	$9,834	$512
	B. Medicare Part B Outpatient & Carrier Expenditures			
	Procedures ($)	Professional services ($)	Pharmaceuticals ($)	Testing & Imaging ($)
HIT adoption	−35.90	33.09	−92.04**	−4.36
	(41.36)	(24.71)	(46.34)	(27.45)
Mean dep. var.	$2,981	$3,116	$1,103	$2,500

Notes: Entries report coefficients and standard errors from 8 separate regressions. The dependent variables are indicated in the column labels. In each regression, HIT adoption is the key explanatory variable of interest.

In panel A: column 1 reports results on the natural log of inpatient hospital spending billed through Medicare Part A; column 2 reports the number of inpatient stays within 1 year of the initial admission; column 3 reports the natural log of average inpatient hospital spending on subsequent stays for patients who are readmitted within 1 year; column 4 reports average spending on emergency care in dollars. In panel B, all spending is measured in dollars.

In panel B: column 1 reports spending on procedures and surgeries; column 2 reports spending on professional services (including physician bills); column 3 reports spending on pharmaceuticals covered through Medicare Part B; column 4 reports spending on testing and imaging.

Regressions control for hospital fixed effects, state-year fixed effects, a differential time trend amongst HIT adopting hospitals, time trends that vary by quartile of hospital size, trauma hospital status, hospital investment in CT, PET and MRI scanners, as well as patient age (in 1-year bins), sex, race, and primary diagnosis code.

An observation is a hospital-year, 1998-2004. There are 27,317 observations. Regressions are weighted by the number of patients and standard errors are clustered by hospital.

*** denotes significance at 1 percent level;

** at 5 percent level;

* at 10 percent level.

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Table 4

Effect of HIT Adoption on Intensity and Quality of Care

	(1)	(2)	(3)	(4)
	A. Intensity of Care			
	Log(length of stay)	Log(number of physicians)		Standardized intensity composite
HIT adoption	0.00087	0.00356		0.00569
	(0.00268)	(0.00487)		(0.00841)
Mean of dep. var.	6.9	13.3		
	B. Quality of Care			
	30-day readmission rate	Rate of medical complication	Rate of adverse drug events	Standardized quality composite
HIT adoption	−0.00126	−0.00181	0.00143*	−0.00332
	(0.00097)	(0.00114)	(0.00074)	(0.01440)
Mean of dep. var.	0.0843	0.065	0.016	

Notes: Entries are parameter estimates and clustered standard errors (in parentheses). The dependent variables are indicated in the column labels.

Results reported in column 4 combine estimates from the previous columns to calculate a standardized composite effect.

Regressions control for hospital fixed effects, state-year fixed effects, a differential time trend amongst HIT adopting hospitals, time trends that vary by quartile of hospital size, trauma hospital status, hospital investment in CT, PET and MRI scanners, as well as patient age (in 1-year bins), sex, race, and primary diagnosis code. An observation is a hospital-year, 1998-2004. There are 27,317 observations. Regressions are weighted by the number of patients and standard errors are clustered by hospital.

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Table 5

Threats to Validity: Patient Selection & Hospital Investments

	(1)	(2)
	A. Patient characteristics: omnibus tests	
	Patient demographics: age, race, sex	Patient diagnosis indicator variables
p-value	0.500	0.967
	B. Hospital investments: regression results	
	Technology index	Trauma hospital
HIT adoption	−0.00626	−.032433**
	(0.02804)	(0.01436)
Mean dependent variable	1.685	0.301
	C. Staffing inputs: regression results	
	Log(number of full time employees)	Log(number of full time nurses)
HIT adoption	0.01489	0.01112
	(0.00933)	(0.01018)
Mean dependent variable	954	240

Notes: Panel A presents p-values from an omnibus test that tests the joint significance of the HIT adoption variable across equations. In column 1, dependent variables are patient demographic characteristics. In columns 2, dependent variables are indicator variables for each in-sample diagnosis.

The entries in panels B and C report the coefficients and standard errors from 4 separate regressions, where the dependent variable is noted in the column labels.

Each regression controls for hospital fixed effects, state-year fixed effects, a differential time trend amongst HIT adopting hospitals, time trends that vary by quartile of hospital size, as well as patient age (in 1-year bins), sex, race, and primary diagnosis code. An observation is a hospital-year, 1998-2004. There are 27,317 observations. Regressions are weighted by the number of patients and standard errors are clustered by hospital.

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Table 6

Impact of Ancillary HIT System Adoption

	Log(medical expenditures)	Patient mortality	Standardized intensity composite	Standardized inpatient quality composite
	(1)	(3)	(5)	(7)
	A. Impact of Computerized Physician Order Entry			
CPOE adoption	0.03054***	0.00343	0.00637	0.01341
	(0.00971)	(0.00266)	(0.02041)	(0.01467)
Mean dep. var.	$44,385	0.0993		
	B. Impact of Computerized Physician Order Entry, Laboratory Info. Sys, & Radiology Info. Sys.			
CPOE, LIS, RIS	0.01555**	0.00188	0.00847	−0.01403
	(0.00732)	(0.00193)	(0.01586)	(0.01056)
Mean dep. var.	$44,385	0.0993		

Notes: Entries are coefficient estimates and clustered standard errors. The dependent variables are indicated in the column labels. For these results, the usual explanatory variable is replaced with an indicator variable for the adoption of computerized physician order entry (CPOE) in panel A or the simultaneous adoption of CPOE, a laboratory information system, and a radiology information system in panel B.

Results reported in column 3 combine estimates from two separate regressions with dependent variables of log(length of stay) and number of physicians consulted to estimate a standardized intensity composite effect. Results reported in column 4 combine estimates from three separate regressions with dependent variables of readmission rate, medical complications, and adverse drug events to estimate a standardized quality composite effect.

Each regression controls for hospital fixed effects, state-year fixed effects, a differential time trend amongst CPOE adopting hospitals, as well as time trends that vary by quartile of hospital size. Additional controls include: patient age (in 1-year bins), sex, race, primary diagnosis, hospital's investment in CT, MRI, and PET scans, and trauma hospital status. An observation is a hospital-year, 1998-2004. There are 27,317 observations. Regressions are weighted by the number of patients and standard errors are clustered by hospital.

*** denotes significance at 1 percent level;

** denotes significance at 5 percent level;

* denotes significance at 10 percent level.