Deconstructing the Health IT Adoption Paradox

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1. Introduction

The past decade has been characterized by significant optimism about the the role of health IT in improving quality and lowering costs. In 2004, the Bush administration set a goal for most Americans to have their health information stored in an electronic medical by 2014. Health IT also occupies a central place in the Obama administration's health reform efforts. The American Recovery and Reinvestment Act of 2009 allocates $19.5 billion for investment in Health IT. The government of the United States plans to computerize all health records within five years; at an estimated cost of between $75 to $100 billion (CNN, Jan 12 2009). Recently, the Brookings Institute published an influential report targeting at "bending the curve" of healthcare cost, and Health IT is listed as the first recommendation to achieve this goal (Antos et al, 2009).

The momentum to increase the uptake of health IT presents an intriguing anomaly. On the one hand, the rationale for increasing investment is supported by a growing body of evidence. Several studies in IS have demonstrated that certain HIT investments can increase revenue, improve quality, and lower costs (Amarasingham et al., 2009; Devaraj and Kohli, 2000, 2003; Kohli and Devaraj, 2004). The Institute of Medicine's early reports (1999, 2004) estimated that Health IT could significantly reduce clinical errors and save lives.

On the other hand, hospitals and physicians are lagging behind in their adoption of health IT. Significant concerns and criticism have been expressed related to the speed of IT penetration in the healthcare industry (as a point of comparison, mining is the only other industry that is behind healthcare in using IT). It is widely believed that the 2014 goal set up by Bush will not be met. Recent studies (Desroches 2008, Jha et al 2009) show that the health IT adoption rate samong physicians and hospitals are strikingly low.

This scenario in health IT adoption is in sharp contrast with the IT productivity paradox. In the 1980s, business invested in IT enthusiastically, while researchers experienced difficulty in proving the value of the investment (Brynjolfsson 1993, Brynjolfsson and Hitt 1996). Here we observe exactly the opposite. Despite evidence from a variety of research studies about the benefits of health IT, most hospitals are quite passive in investing, even with strong external pressure and advocacy by the government. We term this phenomenon "*the Health IT adoption paradox*".

This paper seeks to provide initial evidence that would help resolve this paradox. We propose one explanation: that the current positive evidence is largely produced by HIT advocate institutes, which have superior IT capability and performance as well. As evident in a recent review paper by Chaudhry et al. (2006), of the 257 studies included in this review, approximately 25% focused on internally developed applications, 72% are in-house developed systems, while only 3% studies included commercially developed systems. Hospitals that can afford to develop Health IT internally typically have superior technology capacity, stronger leadership, a supportive organizational culture, and abundant financial resources. In other words, they are quite different from the majority of "other" hospitals. Therefore, the findings based on these elite hospitals might not be readily generalized. It is likely that hospitals that are less sophisticated in IT experience greater challenges in appropriating the benefits of health IT. This, in turn, might cause them to be reluctant to invest in Health IT.

Using a nation-wide data set that spans multiple years, we find evidence that HIT improves quality; however the benefits largely accrue to academic hospitals, which constitute a very small portion of all the hospitals in US. This suggests that while health IT undoubtedly has some value for adopters, the value for non-adopters is likely less than promised by health IT advocates. We suggest the key to facilitating and accelerating wide-spread adoption of health IT is to figure out how to make HIT work in hospitals which are already lagging behind.

2. Data

We obtained hospital quality measures from Hospital Quality Alliance (HQA), which is the largest national public–private collaboration to collect hospital data regarding the quality of care (Jha et al. 2005). Our health IT measures come from HIMSS Analytics. Our third dataset is the American Hospital Association (AHA), which publishes annual surveys on hospitals. The sample is comprised of 3401 acute care, non-federal, US hospitals with a panel from 2004 to 2007.

For quality measures, we focus on four measures related to pneumonia. We choose pneumonia because of the pervasiveness and the severity of the disease, which can adequately reflect the care quality of a hospital. These measures have been shown to reflect a hospital's quality performance on metrics such as mortality rates in randomized trials with controlled populations (Jha et al. 2007). Further, as hospitals were given a strong financial incentive from the Centers for Medicare and Medicaid Services, the largest single healthcare payor in the US, to report these measures, we have data for most hospitals, which allows for a more meaningful comparison between HIT adopters and non adopters. The four measures are: Percentage of Pneumonia Patients Assessed and Given Pneumococcal Vaccination (*PN1*); Percentage of Pneumonia Patients Whose Initial Emergency Room Blood Culture Was Performed Prior To The Administration Of The First Hospital Dose Of Antibiotics(*PN2*); Percentage of Pneumonia Patients Given Smoking Cessation Advice/Counseling (*PN3*); and Percentage of Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s) (*PN4*).

Our health IT measures are construct based on the adoption of Electronic Medical Record (EMR) and Computerized Physician Order Entry (CPOE) systems. These two systems are among the core components of hospital health, and have been extensive examined in clinical journals.

We get extensive institutional measures from the AHA annual survey. These include the size of hospitals, location, academic status, patient composition, for-profit status, and patient volume. These variables have been found to be associated with quality of hospitals, and serve as control variables in the empirical model.

3. Analysis

We apply the following empirical model to examine the relationship between health IT and hospital quality of care:

$$\begin{aligned} Quality_{it} = {} & \beta_0+\beta_1*HIT_{i,t-1} +\beta_2*CDVOL_{it} + \beta_3*STFBD_{it} + \beta_4*ADJADM_{it} + \beta_5*MDCARE_{it} + \\ & \beta_6*MDCAID_{it} + \beta_7*FTNPB_{it} + \beta_8*ACADEMIC_{it} + \beta_9*SYS_{it} +\beta_{10}*FPROFIT_{it} +\beta_{11}*GOV_{it} \\ & + \beta_{12}*RURAL_{it} +YEAR+ \xi_{it} \end{aligned}$$

In the above regression, Quality is measured by four variables defined in the previous section (*PN1-PN4*). We define *HIT* as an indicator equal to one for hospitals that have both EMR and CPOE and zero otherwise. This variable is lagged by one year to allow health IT to affect quality of care.

For control variables, *CDVOL* is the number of condition-specific patients, corresponding to each dependent variable. We have two size controls at the hospital level: the number of staffed beds (*STFBD*) and the number of adjusted admission (*ADJADM*). Patient composition is reflected in two variables: the percentage of Medicaid (MDCAID) and the percentage of Medicare (MDCARE). It has been found that shortage of nurses can negatively influence quality, thus we include the number of full-time nurses per staffed bed (FTNPB). We use a dummy variable to indicate whether a hospital is an Academic hospital by COTH membership (ACADEMIC). Another dummy variable SYS is used to indicate whether the hospital belongs to a multi-hospital system. The hospital's owner ship is reflected in two variables: for-profit or not (FPROFIT) and owned by Government or not (GOV). We use the dummy variable RURAL to indicate whether a hospital is located in rural or urban areas. Finally, year dummies (YEAR) are added to control for the temporal changes in quality across years.

In the above model, continuous variables that are measured as levels (*CDVOL, STFBD,* and *ADJADM*) are transformed by natural logarithm.

We are fairly confident that the above model includes most of the confounding factors that have been associated with quality in the literature. Nonetheless, there is a legitimate concern that hospitals' choice of HIT adoption might be endogenous. Although fully resolving this issue will require a well-specified behavior model, in this study we exploit the advantages offered by our panel data structure to estimate a fixed effects model. The fixed effects should capture hospital-specific heterogeneity in quality. Therefore, our findings should be less susceptible to the reverse causality concern. Table 1 provides the summary statistics of major variables.

Table 1 Summary Statistics of Major Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
HIT (CPOE and EMR)	16767	0.068	0.253	0	1
PN1(Pneumococcal Vaccination)	12353	0.658	0.249	0	1
PN2(Blood Culture)	11764	0.867	0.093	0	1
PN3(Smoking Cessation)	11720	0.799	0.223	0	1
PN4(Appropriate Initial Antibiotic)	12303	0.811	0.129	0	1
STFBD (# of staffed bed)	16765	190.29	168.66	3	1757
ADJADM (# of adjusted admission)	16767	15838.14	14256.66	29	156582
PMCARD (% of Medicare patients)	14158	0.489	0.192	0	1.092
PMCAID (% of Medicaid patients)	14138	0.199	0.172	0	1.323
FTNPB (# of nurses per bed)	16765	1.454	2.670	0	326.9
IACAD (dummy for academic status)	16767	0.084	0.278	0	1
SYS (dummy for belonging to a hospital system)	16767	0.663	0.472	0	1
FPROFIT (dummy for for-profit hospital)	16767	0.166	0.372	0	1
GOV (dummy for government-owned hospital)	16767	0.156	0.363	0	1
RURAL (dummy for rural location)	16767	0.337	0.472	0	1

Below we first report the cross-sectional estimation in Table 2. Because there are multiple observations from each hospital, clustered standard errors are applied, which are robust to autocorrelation among errors across years. Interestingly, we find that the coefficient of HIT is marginally significant (p<0.1) in only one of the four quality measures (*PN3*). However, more interesting patterns are revealed after we control for the hospital-specific factors in the fixed effects model (Table 3). We find that HIT is significantly associated with two of the four quality measures (*PN1* and *PN4*), at p<0.05 and p<0.01 respectively.

A comparison of the cross-sectional and fixed effects estimation sheds light on one important question. It has often been suggested that the positive correlation between health IT and quality might be an outcome of the fact that high quality hospitals are more likely to adopt Health IT. Our results suggest that, conditional on other factors that influence healthcare quality, the reverse causality argument is not supported. Rather, we find that health IT indeed contributes to quality improvement. In our estimation period, EMR and CPOE contribute 2.54 percentage points in Pneumococcal Vaccination (PN1), and 1.30 percentage points in patients being given appropriate antibiotics. Thus based on a large scale sample, we find a positive impact of HIT on certain healthcare quality, consistent with Parente and McCullough (2009).

Table 2 Cross Sectional Estimation

	(1)	(2)	(3)	(4)
VARIABLES	**pn1**	**pn2**	**pn3**	**pn4**
HIT (one year lag)	0.0142	-0.00428	0.0155*	-0.00574
	(0.00914)	(0.00353)	(0.00801)	(0.00461)
Log (STFBD)	-0.0202**	0.00670**	0.000408	-0.0186***
	(0.00978)	(0.00342)	(0.00935)	(0.00410)
Log(ADJADM)	-0.00731	-0.0234***	0.00775	-0.0187***
	(0.0119)	(0.00423)	(0.0112)	(0.00490)
PMCARD	-0.0126	-0.00807	0.0708***	-0.00951
	(0.0261)	(0.0134)	(0.0253)	(0.0117)
PMCAID	-0.125***	-0.0592***	-0.000301	-0.0871***
	(0.0293)	(0.0134)	(0.0269)	(0.0130)
FTNPB	0.00885	0.00755***	-0.00628	-0.00322
	(0.00579)	(0.00192)	(0.00566)	(0.00247)
ACADEMIC	-0.0464***	-0.0184***	-0.0546***	-0.0292***
	(0.0127)	(0.00489)	(0.0108)	(0.00642)
SYS	0.0264***	0.00231	0.0154**	0.0150***
	(0.00710)	(0.00258)	(0.00618)	(0.00312)
FPROFIT	-0.0406***	-0.0164***	0.0113	-0.0393***
	(0.00883)	(0.00314)	(0.00741)	(0.00420)
GOV	-0.0385***	-0.0231***	-0.0205**	-0.0280***
	(0.0101)	(0.00434)	(0.00937)	(0.00458)
RURAL	0.0390***	0.00649**	-0.00508	0.0219***
	(0.00803)	(0.00280)	(0.00709)	(0.00349)
CDVOL	0.0491***	0.0122***	0.0643***	0.0115***
	(0.00711)	(0.00311)	(0.00518)	(0.00389)
Constant	0.406***	0.964***	0.416***	1.178***
	(0.0663)	(0.0245)	(0.0660)	(0.0270)
Observations	10118	9655	9609	10087
R-squared	0.337	0.232	0.257	0.467

Other controls: year dummy variables
Clustered standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 Fixed Effects Estimation

	(1)	(2)	(3)	(4)
VARIABLES	**pn1**	**pn2**	**pn3**	**pn4**
HIT (one year lag)	0.0254**	0.00229	0.0155	0.0130***
	(0.0108)	(0.00509)	(0.0125)	(0.00500)
Log (STFBD)	0.0269	-0.0119	0.0169	0.0262***
	(0.0223)	(0.0109)	(0.0282)	(0.00995)
Log(ADJADM)	0.0157	0.000475	-0.0352	0.00295
	(0.0204)	(0.0144)	(0.0229)	(0.00883)
PMCARD	0.00170	-0.00383	-0.00895	0.0107
	(0.0344)	(0.0146)	(0.0396)	(0.0163)
PMCAID	0.137***	0.00387	-0.0331	0.000447
	(0.0432)	(0.0233)	(0.0592)	(0.0224)
FTNPB	0.000942	-0.00685**	0.00509	0.00356
	(0.00645)	(0.00338)	(0.00831)	(0.00385)
ACADEMIC	0.0712**	-0.00516	0.0274	0.00337
	(0.0281)	(0.0121)	(0.0292)	(0.0124)
SYS	-0.000688	-0.00102	0.00438	0.0125*
	(0.0153)	(0.00687)	(0.0180)	(0.00712)
FPROFIT	0.00375	-0.00358	0.0172	-0.0144
	(0.0226)	(0.0110)	(0.0288)	(0.0103)
GOV	-0.0288	-0.0237**	-0.00554	-0.0101
	(0.0316)	(0.00976)	(0.0279)	(0.0145)
CDVOL	-0.0156*	-0.00228	0.00876	-0.0229***
	(0.00852)	(0.00454)	(0.00822)	(0.00434)
Constant	0.576***	0.904***	1.113***	0.864***
	(0.218)	(0.137)	(0.248)	(0.0969)
Observations	10118	9655	9609	10087
R-squared	0.548	0.342	0.351	0.639
Number of newid	3048	3011	3011	3050

Other controls: year dummy variables

Clustered standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

We next examine what types of hospitals drive the above finding. As most early findings on the positive impacts of health IT are based on academic institutes, we hypothesize that these hospitals, which tend to be thought-leaders and typically resource-abundant, might gain the most from HIT. To test this hypothesis, we add the interaction term between HIT and ACADEMIC, into the empirical model:

$$Quality_{it} = \beta_0 + \beta_1 * HIT_{i,t-1} + \beta_2 * HIT_{i,t-1} * ACADEMIC_{it} + \beta_3 * CDVOL_{it} + \beta_4 * STFBD_{it} + \beta_5 * ADJADM_{it} + \beta_6 * MDCARE_{it} + \beta_7 * MDCAID_{it} + \beta_8 * FTNPB_{it} + \beta_9 * ACADEMIC_{it} + \beta_{10} * SYS_{it} + \beta_{11} * FPROFIT_{it} + \beta_{12} * GOV_{it} + \beta_{13} * RURAL_{it} + YEAR + \xi_{it}$$

The estimates are reported in Table 4. Interestingly, we find that the interaction term is statistically significant in both *PN1* and *PN4* regressions. HIT, on the other hand, becomes insignificant. The results suggest that among the adopters, the academic hospitals, which constitute 8% in our sample, gain the most from HIT with respect to quality improvement. The rest of the adopters do not enjoy significant benefit, as reflected in the coefficient of HIT, which is close to zero. It is also interesting to note that the magnitude of the interaction term is also large, more than doubling the average effects of HIT estimated in Table 3. Overall this finding supports our initial conjecture that hospitals gain unequally from their investments in health IT.

Table 4 Moderating Effects Estimation

	(1)	(2)	(3)	(4)
VARIABLES	**pn1**	**pn2**	**pn3**	**pn4**
HIT (one year lag)	0.0137	0.00114	0.0109	0.00684
	(0.0119)	(0.00559)	(0.0137)	(0.00545)
HIT*ACADEMIC	0.0610**	0.00637	0.0251	0.0320**
	(0.0260)	(0.0125)	(0.0311)	(0.0125)
Log (STFBD)	0.0264	-0.0119	0.0167	0.0260***
	(0.0223)	(0.0109)	(0.0282)	(0.00994)
Log(ADJADM)	0.0153	0.000454	-0.0352	0.00270
	(0.0204)	(0.0144)	(0.0229)	(0.00882)
PMCARD	0.00165	-0.00382	-0.00898	0.0106
	(0.0343)	(0.0146)	(0.0396)	(0.0163)
PMCAID	0.136***	0.00382	-0.0333	8.08e-05
	(0.0431)	(0.0233)	(0.0591)	(0.0223)
FTNPB	0.000995	-0.00685**	0.00506	0.00358
	(0.00644)	(0.00338)	(0.00831)	(0.00385)
ACADEMIC	0.0678**	-0.00550	0.0261	0.00158
	(0.0277)	(0.0122)	(0.0291)	(0.0123)
SYS	-0.00131	-0.00105	0.00424	0.0122*
	(0.0154)	(0.00687)	(0.0180)	(0.00714)
FPROFIT	0.00377	-0.00356	0.0173	-0.0144
	(0.0227)	(0.0110)	(0.0288)	(0.0103)
GOV	-0.0282	-0.0236**	-0.00537	-0.00979
	(0.0316)	(0.00975)	(0.0279)	(0.0145)
CDVOL	-0.0150*	-0.00221	0.00890	-0.0224***
	(0.00850)	(0.00454)	(0.00821)	(0.00434)
Constant	0.580***	0.904***	1.114***	0.866***
	(0.218)	(0.137)	(0.248)	(0.0968)
Observations	10118	9655	9609	10087
Number of newid	3048	3011	3011	3050
R-squared	0.549	0.342	0.351	0.639

Other controls: year dummy variables
Clustered standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

4. Conclusion and Discussion

In summary, we find that health IT has a meaningful and significant impact on quality of care. Further, the impact of health IT is contingent on the type of hospital. Academic hospitals gain the most, while Health IT has insignificant effects on the rest of adopters. Therefore, our results illuminate the Health IT adoption paradox. Since most average hospitals do not see a tangible benefit from health IT investment, it is not surprising they are reluctant to adopt Health IT.

This finding has important policy implications. Rather than mandating the use of health IT in hospitals, policy makers in government and executives in the health IT industry together should focus on helping hospitals to better utilize their investments. There is a great need to understand the mechanisms for hospitals through which hospitals can assimilate new information technologies more effectively into their daily operations. Our work thus urges scholars in this area to focus efforts on opening the “black box” of health IT and more fully explicating the processes through which investments are reflected in productivity gains.

In the above analysis, we use academic status as a proxy for a hospital’s leadership in health. We are in the process of constructing direct measures of hospital’s IT competence, and examining other quality measures and moderating factors, which we hope to present at WISE this year. (References omitted due to space limit)