

## Network Effects of Health Information Technology: Evidence from California Hospitals\*

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*A number of studies have investigated the factors affecting health information technology (IT). However, these studies have not focused on the possibility that some products have more value when others are using them as well. The importance of this network effect has been widely recognized in IT industry organizations as well as in other sectors. However, few empirical studies have looked at the network effect in health IT adoption. This paper examines the impact of neighbor hospitals' IT capital adoption and IT labor employment on a hospital's IT capital adoption, using the California Office of Statewide Health Planning and Development (OSHPD) data from 2000 to 2007. Findings show that neighbor hospitals' IT capital adoption and IT labor employment were associated with an increase in a hospital's IT capital adoption. This network effect varied across hospital characteristics.*

JEL Classification: I11, I15, L22

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### I. Introduction

Health information technology (IT) has a number of potential benefits: IT can improve health care quality, prevent medical errors, reduce health care costs, decrease paperwork, increase administrative efficiencies, and expand access to affordable care (IOM, 2001, 2005; Kuperman and Gibson, 2003; Garg et al., 2005; Chandhry et al., 2006; Parente and Van Horn, 2007; Furukawa et al., 2008; Borzekowski, 2009; Parente and McCullough, 2009; McCullough et al., 2010). Despite these potential benefits, the adoption rate of health IT is lower in the United States than in other industrialized countries, including Canada, Germany and the United Kingdom (Anderson et al., 2006). Only 37 percent of community hospitals reported moderate or high use of health IT in 2005 (AHA, 2007). For

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example, even though Computerized Physician Order Entry (CPOE) is believed to promote patient safety (IOM, 1999), in 2004, only 7 percent of hospitals had installed CPOE and another 9 percent had contracted for it (Fonkych and Taylor, 2005). A more recent study showed that in 2008 only 1.5 percent of U.S. hospitals had a comprehensive electronic health record (EMR) system and an additional 7.6 percent had a basic EMR system (Jha et al., 2009). These low adoption rates call for an investigation into the factors affecting health IT adoption.

Investigating the factors affecting health IT adoption can provide a better understanding of these adoption rates and can possibly suggest strategies to increase them. A number of studies have investigated the factors affecting health IT adoption in specific areas, such as radiology, laboratory, and CPOE. These studies reported several influential factors affecting health IT adoption, such as hospital characteristics, financial factors, and environmental factors (Borzekowski, 2002; Cutler, Feldman, and Horwitz, 2005; Wang et al., 2005; Capps and Cuellar, 2007; McCullough, 2008; Furukawa et al., 2008).

However, these studies did not account for interactions with other hospitals in a hospital's adoption of health IT. In other words, these studies did not focus on the possibility that some IT products are more valuable when others are using them as well. For example, when the fax machine was introduced, its value depended on how many others were using the same technology. Thus, the utility that a user or a consumer derives from the consumption of a good may depend on the number of other users of the good (Katz and Shapiro, 1986).

Following the first study of the so-called "network effect" in long-distance telephone use (Rohlf, 1974), the network effect has been widely recognized as an important factor in the organization of IT industries and in IT sectors including databases, network equipment, and DVD players (Gandal, 1995; Brynjolfsson and Kemerer, 1996; Dranove and Gandal, 2003). In particular, the network effect has been found to directly and indirectly affect technology adoption through learning spillover (Goolsbee and Klenow, 2002; Gowrisankaran, 2004; Akerberg and Gowrisankaran, 2006; Ryan and Tucker, 2008; Tucker, 2008).

Firms may make IT investment decisions based on a competitor's IT adoption. For example, when a firm introduces IT, competing firms will have greater difficulty recouping their IT investment. This adoption behavior is called the first-mover advantage. Conversely, later adopters may learn how to use IT by observing the early adopters, this behavior is called the second-mover advantage. Other economic studies have shown that IT adoption involves interactions with other firms (Saloner and Shepard, 1995; Majumdar and Vankataraman, 1998; Hall and Khan, 2003). These network effects may help to increase the rate of IT adoption by fostering technology learning or by enhancing the technology.

However, there is little empirical evidence regarding network effects in health IT adoption, even though network externalities are common in IT (Hall and Khan,

2003). The benefits that a hospital derives from adopting health IT may increase with the total adoptions of health IT systems in hospitals, because the hospitals will be able to share test results and patient records as more hospitals adopt health IT. Because prospective payment systems (PPS), such as Medicare and Medicaid, reimburse hospitals at a flat rate, hospitals may have financial incentives to share patient records and test results in order to avoid duplicate tests. Moreover, using health IT to exchange electronic patient information is faster and more reliable than exchanging patient information via paper records.

This paper examines the network effect in the adoption of health IT. In particular, this paper investigates the relationship between a hospital's health IT capital adoption and their neighbor hospitals' health IT capital adoption and IT labor employment, using the California Office of Statewide Health Planning and Development (OSHPD) data from 2000 to 2007.

## **II. Background**

Several studies have examined the factors affecting health IT adoption. Earlier studies were mostly interested in the financial factors. Borzekowski (2002) investigated the relationship between health care financing and health IT adoption and found that, in the 1970s, state price regulations deterred the adoption of health IT. However, by the early 1980s, hospitals adopted more health IT in response to the implementation of Medicare's PPS. Hospitals interested in lower costs were more likely to adopt health IT. Cutler et al. (2005) examined slow CPOE adoption in hospitals, using data on CPOE ownership from the Leapfrog Group from 2002 to 2003. They concluded that CPOE adoption was unlikely to increase because hospital executives did not perceive a financial benefit from the technology. The researchers also suggested that the favorable effect from reimbursement may increase CPOE adoption in the short term.

Wang et al. (2005) also found that organizational factors were influential. Using 1998 Health Information Management Systems Society (HIMSS) data, the researchers explored the effects of the hospital market, organizational factors, and financial factors on the adoption of health IT, including clinical, administrative, and managerial information systems. They found that large, system-affiliated, for-profit hospitals were more likely to adopt managerial information systems. They also found that operating revenue was positively associated with health IT systems. The researchers concluded that organizational and financial factors in hospitals affected the adoption of clinical, administrative, and managerial information systems.

Recent studies have focused on a broader range of factors in health IT adoption, including competition and strategic behavior. Capps and Cuellar (2007) used

HIMSS data from 1999 to 2002 to investigate how market and hospital characteristics influence the adoption of quality-improving health IT. They found that higher levels of competition were associated with lower adoption rates of quality-improving health IT. Similarly, McCullough (2008) estimated the effect of market structure, hospital structure and strategic behavior on basic health IT adoption, including in radiology, pharmacy, and laboratory systems. He found that system hospital, percentage of Medicare and Medicaid patients, and hospital scale of service were associated with health IT adoption, but strategic behavior, hospital competition, and ownership were not.

Furukawa et al. (2008) analyzed the impact of medication safety, organizational factors and financial factors on health IT adoption. The results showed that hospital size, ownership, teaching status, system membership, payer mix, and accreditation status affected health IT adoption. Also, the researchers found that hospitals in states with a patient safety initiative had higher health IT adoption rates. The most recent study examined the effect of state privacy regulations on the diffusion of EMR (Miller and Tucker, 2009). The study found that state privacy regulations restricting the release of health information reduced hospital EMR adoption by more than 24 percent. The study suggested that this reduction comes from the suppression of network externalities.

These previous studies focused on hospital characteristics, financial factors, organizational factors, and environmental factors. However, little attention has been paid to the role of network effects in health IT adoption. Because there is a lot of interaction among the technologies, the network effect may play a significant role in health IT adoption. Previous studies focused on specific IT applications, such as CPOE or EM, (Kuperman and Gibson, 2003; Garg et al., 2005; Chandhry et al., 2006; Parente and Van Horn, 2007; Furukawa et al., 2008; Borzekowski, 2009; Parente and McCullough, 2009; McCullough et al., 2010). In this study, health IT is measured by the dollar amount spent, as shown on the hospital's balance sheet. Karshenas and Stoneman (1993) reported that utilizing price produces a more theoretically rigorous model of process innovation diffusion. This paper examines the effect of neighbor hospitals' IT capital adoption and IT labor employment on a hospital's health IT capital adoption and it also examines the variation in this network effect across different hospital characteristics.

### III. Data

This study employed hospital- and patient-level data from OSHPD from 2000 to 2007. California is the largest state that requires hospitals to report their financial data, as a result, the state provides the most comprehensive source of hospital financial data. Comprehensive and accurate hospital financial data on a national

scale are not available (Magnus and Smith, 2000). Within the last four months of their fiscal year, California hospitals must submit an annual financial report to the OSHPD that includes a detailed income statement, balance sheet, statements of revenue and expenses, and supporting schedules. These financial reports are based on a uniform accounting and reporting system developed and maintained by OSHPD. The hospital-level data also provide characteristics such as ownership type, bed size, system affiliation, and teaching status. In addition, it includes information on the hospital's health IT expenditure and depreciation, which I used to construct measures of health IT capital and health IT labor.

Patient level data, including inpatient discharge or outpatient encounter visit records are reported on a scheduled basis for each time a patient is treated in a licensed general hospital, emergency department, or ambulatory care surgery center in California. This data includes patient demographic information, as well as clinical and administrative information, such as diagnosis, disposition, total charges, length of stay, admission type, and payer source for all hospitalized patients. Based on this rich data set, many studies utilize this OSHPD data (Lee et al., 2013; Song et al., 2013; Reiter and Song, 2011; Song and Reiter, 2010).

The unit of analysis is acute care California hospitals. There are about 260 hospitals for each year of data. Hospitals total 2,045 over 8 years and the data set is an unbalanced panel. Kaiser Permanente-owned hospitals were excluded because they were not required to report financial data to OSHPD. For data consistency, hospitals whose balance sheets covered fewer than 365 days or more than 366 days were dropped. Also, all figures were converted to year 2007 dollars using the GDP deflator.

### 3.1. IT Capital and IT Labor

The OSHPD data placed all IT expenditures within the "data processing" section of the hospital's financial statement. Health IT capital and IT labor were extracted from each hospital's balance sheet (Lee et al., 2013). Health IT capital adoption was defined as follows:

$$K = \text{Physical Capital} + \text{Purchased Service} + \text{Lease \& Rental} + \text{Other Direct Expenditure} \quad (1)$$

Where physical capital represents the hardware, purchased service represents the outsourced IT,<sup>1</sup> and lease and rental represent the licensing of software. OSHPD

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<sup>1</sup> I recognize that purchased services may include both capital and labor inputs. However, the data do not provide the details necessary to disentangle the component inputs; qualitative work suggests that this is mostly a capital measure.

only reported depreciation of health IT physical capital. Thus, to reconstruct the actual physical capital, I used the 5-year straight-line method of depreciation (Gapenski, 2007).

$$\begin{aligned} &\text{IT labor employment was expenditure in data processing and defined as} \\ &L = \text{Salaries \& Wages} + \text{Employee Benefit} + \text{Professional Fees} \end{aligned} \quad (2)$$

Both health IT capital adoption and IT labor employment were measured in dollars.

## 3.2. Explanatory Variables

### 3.2.1. Network Effect

The key variables are neighbor hospitals' IT capital adoption and IT labor employment. Hospitals may invest more in health IT in response to their neighbor hospitals' IT adoption behavior because the hospitals will be able to improve utility and reduce cost by sharing the test results and patient records. IT adoption of neighbor hospitals was defined as the neighbor's providers' IT within a 20-mile radius, stratified as IT capital adoption and IT labor employment. According to Chou et al. (2009), in 2005, the average distance from a patients' residence to the closest hospital was around 10 miles, while the average distance to the admitting hospital was 31 miles. Thus, I averaged these two numbers to examine the network effects.<sup>2</sup> To calculate the distance, I used the latitude and longitude information for each hospital location from the American Hospital Association (AHA). Neighbor hospitals' IT capital adoption and IT labor employment were defined as below:

$$\text{IT capital adoption of neighbor hospitals: } \frac{\sum_{i=1}^n K_{IT-i}^* Bed_{-i}}{\sum_{i=1}^n Bed_{-i}} \quad (3)$$

$$\text{IT labor employment of neighbor hospitals: } \frac{\sum_{i=1}^n L_{IT-i}^* Bed_{-i}}{\sum_{i=1}^n Bed_{-i}}, \quad (4)$$

where  $i$  represents the hospital,  $-i$  represents the exclusion of the hospital of interest,  $n$  represents the number of hospitals within a 20-mile radius of each hospital of interest,  $K$  and  $L$  represent IT capital and IT labor, respectively, and  $Bed$  represents the number of licensed beds in a given hospital. The neighbor hospitals' IT capital adoption and IT labor employment were weighted by the number of

<sup>2</sup> Other distances, such as 10 miles and 30 miles, yielded similar results.

licensed beds because hospitals with a large number of beds are more likely to invest in IT. Thus, the IT capital adoption of neighbor hospitals measures the weighted average of the IT capital adoption of competitors within a 20-mile radius of each hospital. Similarly, the IT labor employment of neighbor hospitals measures the weighted average of the IT labor employment of competitors within a 20-mile radius of each hospital.

### 3.2.2. Other Independent Variables

I also controlled for a rich set of hospital characteristics. Competition among hospitals may spur their health IT adoption behavior. Hospitals located in highly competitive markets may have greater incentive to invest in health IT in order to reduce costs. Hospital competition is measured based on the market share of individual hospitals. To calculate the competitiveness of a given geographical market, each hospital's share of patient discharges was calculated. Then, these shares were squared and summed to form the Herfindal-Herschman Index (HHI). The geographic market was defined as the 20 miles around each hospital. As the regulation matters, the share of the patient population in each hospital that belongs to Medicare and Medicaid were included, which reflects the stringency of state or federal regulations regarding insurance payments, such as prospective payments. Thus, hospitals with a high proportion of Medicare and Medicaid patients are expected to have higher coordination costs, which may increase the return of health IT adoption.

Two variables were employed to measure the hospital size of service: scale and scope. Health IT may be of greater value to a larger volume hospital because of economies of scale. Moreover, costs will increase as the complexity of hospital services increase. Thus, health IT adoption will be more attractive to hospitals with a broader scope of services as well as to hospitals with a larger volume. Scale was measured as the sum of outpatient visits and inpatient admissions. Scope was measured by dividing the number of outpatient visits by the scale (McCullough, 2008).

The case mix index (CMI)<sup>3</sup> was included to control for the average diagnosis-related group (DRG)<sup>4</sup> weight for a hospital's total Medicare volume. It is used to

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<sup>3</sup> The CMI is a measure of the relative cost or resources needed to treat the mix of patients in each licensed California hospital during the calendar year. To calculate the CMI, Medicare Severity-DRG (MS-DRG) and their associated weights, assigned to each MS-DRG by the Centers for Medicare & Medicaid Services was used. Each patient record is assigned an MS-DRG based on the principal and secondary diagnoses, procedures performed, age, the presence of co-morbidities and complications, discharge status, and gender (<http://www.oshpd.ca.gov/HID/Products/PatDischargeData/CaseMixIndex/>).

<sup>4</sup> Diagnosis-related group (DRG) is a system to classify hospital cases into one of 467 original groups. Its intent was to identify the products that a hospital provides. For example, a product could be an appendectomy. DRGs are assigned by a grouper program based on the International Classification of

adjust a hospital's average cost per patient relative to other hospitals.

Health IT labor and the capital statement, measured as hospital assets, were also included. According to Rosenberg (1972), the workers' skill and the capital statement were two important factors in the diffusion of a technology because both played a crucial role in the successful implementation and operation of a new technology. For example, the successful implementation of a new technology might be slow if it required complex skills. Rosenberg also stressed the importance of the capital statement because the initial implementation of a technology needs the appropriate technical capacities and skills to make it successful. Lastly, labor expense, excluding IT labor was included.

## IV. Methods

My strategy to investigate the determinants of health IT was to look at the regression results using the specifications of the form. I employed investment functions with fixed effect and clustering error at the hospital level. This model estimates the influence of health IT capital on IT capital adoption of neighbor hospitals, the IT labor employment of neighbor hospitals, the interaction term of both variables as well as other explanatory variables. The equation is as follows:

$$\begin{aligned}
 K_{it} = & \alpha + \beta_1 HHI_{it} + \beta_2 R_{it} + \beta_3 M_{it} + \beta_4 CMI_{it} + \beta_5 L^T_{it} + \beta_6 L_{it} + \beta_7 A_{it} \\
 & + \beta_8 NC_{it} + \beta_9 NL_{it} + \beta_{10} NC^*_{it} NL_{it} + e_{it} \\
 e_{it} = & f_i + \tau_t + \varepsilon_{it}
 \end{aligned} \tag{5}$$

where  $K$  is the log of health IT capital adoption,  $HHI$  is the Hospital competition,  $R$  is the regulation, including the share of the population that belongs to Medicare and Medicaid,  $M$  is the hospital size, including scale and scope,  $CMI$  is the case mix index,  $L^T$  is the log of health IT labor,  $A$  is the log of the capital statement,  $L$  is the log of labor expense,  $NC$  is the log of neighbor hospitals' IT capital adoption,  $NL$  is the log of neighbor hospitals' IT labor employment and  $NC^*NL$  is the interaction of neighbor hospitals' IT capital adoption and their IT labor employment. The permanent error component ( $e_{it}$ ) includes three parts;  $f_i$  is a time-constant hospital fixed effect,  $\tau_t$  is the time effect, and  $\varepsilon_{ij}$  is the clustered errors. However, in this analysis, the clustering effect in hospitals may induce within hospital dependence. In this case, ordinary least square (OLS) estimates are still unbiased, but standard errors may be downwardly biased in the finite clustered

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Diseases (ICD) diagnoses, procedures, age, sex, discharge status, and the presence of complications or comorbidities. DRGs are standard practice for establishing reimbursements for other Medicare related reimbursements (Centers for Medicare & Medicaid Services).

sample (Nichols and Schaffer, 2007). Thus, this study accounted for the clustering error within hospitals. Further, there may be a potential endogeneity problem in this equation. For example, there may be a time variant of unobserved variables correlated to independent variables. In this case, all estimates of the model may be seriously distorted. Thus, to control endogeneity problems, a system generalized method of moments (GMM) was employed. This system GMM has been applied in many economic studies to control time-variant unobserved variables (Lee et al, 2013; Blundell and Bond, 1998, 2000; Akerberg, 2006, 2007).

## V. Results

The descriptive statistics are presented in Table 1. From 2000 to 2007, the mean annual cost of IT capital adoption was \$6.3 million and the mean annual cost of IT labor employment was \$1.8 million. The mean annual cost of the neighbor hospitals' IT capital adoption was \$4.9 million and the mean annual cost of their IT labor employment was \$1.3 million. Each hospital's average annual total assets were \$166.3 million and each hospital's average annual total labor expense was \$128.1 million. The average annual scale was 153,754 and scope was 90.6%. The average annual CMI was 1.09. The measure of competition was 30.86. The percentage of Medicare and Medicaid patients was 39.05% and 18.14%, respectively.

[Table 1] Descriptive statistics of 260 acute care California hospitals

Variable	Mean	Std. Dev.
IT Capital (million)	\$6.3	\$11.3
IT Labor (million)	\$1.8	\$3.3
IT Capital Adoption of Neighbor (million)	\$4.9	\$4.6
IT Labor Employment of Neighbor (million)	\$1.3	\$1.0
Total Assets (million)	\$166.3	\$231.9
Total Labor Expense (million)	\$128.1	\$146.3
Scale <sup>1</sup>	153,754	159,629
Scope <sup>2</sup>	90.60%	7.01%
CMI	1.09	0.25
Competition	30.86%	18.93%
Percentage of Medicare patients	39.05%	14.54%
Percentage of Medicaid patients	18.14%	13.51%

Note: 1: Scale: the sum of outpatient visits and inpatient admissions.

2: Scope: number of outpatient visits over Scale.

The regressions in Table 2 estimate the influence of a hospital's health IT capital adoption on the neighbor hospitals' health IT capital adoption and IT labor employment, and the interaction term for both variables as well as other explanatory

variables listed above (Equation 5). First, the fixed effect model was adopted as the basic model because the fixed effect model could also control the endogeneity problem. The first column shows the fixed effects regression with clustering error within hospitals. The second column shows the system GMM regression results. As another study concluded (Lee et al., 2013), the fixed effect coefficients were generally lower than the system GMM estimation. This implies that the fixed effect has some limitations in controlling time-varying error terms. Based on the system GMM regression, the specification tests indicated that the first difference removed the serial correlation and was used in the estimation. Also, the Hanson test p-value was .99, indicating that the over-identification restrictions were not rejected.

[Table 2] Regression results

Variables	Fixed Effect	System GMM
HHI	0.313 (0.296)	0.091 (0.455)
% of Medicare patients	-0.532 (0.478)	-1.254* (0.644)
% of Medicaid patients	-0.525 (0.448)	-1.603** (0.701)
Scale <sup>1</sup>	0.000 (0.000)	0.000 (0.000)
Scope <sup>2</sup>	-0.194 (0.653)	0.936 (0.924)
CMI	0.927* (0.491)	0.991** (0.398)
IT labor	0.022 (0.020)	0.001 (0.028)
Capital Statement	0.209** (0.081)	0.201 (0.127)
Labor Expense	-0.867 (0.354)	0.352 (0.231)
IT Capital Adoption of Neighbor	0.675** (0.299)	1.134* (0.582)
IT Labor Employment of Neighbor	0.726* (0.349)	1.258* (0.658)
IT Capital Adoption of Neighbor *	-0.048**	-0.086**
IT Labor Employment of Neighbor	(0.023)	(0.044)
Constant	14.732* (7.553)	

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

1: Scale: the sum of outpatient visits and inpatient admissions.

2: Scope: number of outpatient visits over Scale.

Annual dummies included but not reported, ( ) represent standard error.

HHI, Herfindal-Herschman Index; CMI, case mix index.

These findings show that hospitals may adopt more health IT capital in response to their neighbor hospitals' behavior. The significantly positive coefficients of neighbor hospitals' IT capital adoption and IT labor employment showed that both variables were positively associated with higher IT capital adoption ( $p\text{-value} < 0.1$ ). The regression results showed that the coefficients of neighbor hospitals' IT capital adoption and IT labor employment were 1.134 and 1.258, respectively. This result suggests epidemic diffusion in IT capital.<sup>5</sup> For example, a one dollar investment in a neighbor hospital's health IT capital adoption was associated with a \$1.13 increase in a hospital's IT capital adoption. Similarly, a one dollar investment in a neighbor hospital's health IT labor employment was associated with an almost \$1.26 increase in a hospital's IT capital adoption. However, the interaction of a neighbor hospitals' IT capital adoption and IT labor employment was associated with lower health IT capital adoption. This result indicates that the neighbor hospitals' IT capital adoption and their IT labor employment substituted for each other. Thus, these results show a positive network effect in health IT adoption.

Because California is a very large state, the number of hospitals within 20 miles area varies from 1 to 97; mean 27; standard deviation 29. Thus, this variation may cause bias in the estimation results. To account for this variation, the samples were separated into two subsamples based on their median (less than 20 hospitals and more than or equal to 20 hospitals within 20 miles area) and compared the estimation regressions with the full sample system GMM. However, any significant difference between them was not found (first and second columns in the appendix Table 1). Also, a higher number of hospitals within 20 miles (higher density) led to a larger effect on health IT capital adoption. I also dropped the areas which had the 10% lowest and the 10% highest number of hospitals within 20 miles to control for outliers. But, the results were similar (appendix Table 2).

Other factors positively associated with health IT capital adoption were fewer Medicare and Medicaid admissions and CMI. Then, I examined how this network effect varied across hospital characteristics by stratifying such characteristics as capital statement, ownership, teaching status and system member status.

## 5.1. Hospital Characteristics

### 5.1.1. Capital Statement

Capital statement was an important factor in the diffusion of a technology because it played a crucial role in the successful implementation and operation of a new technology. Thus, I stratified capital statement by lower (less than median [\$91 million]) and higher (more than median). The regression results (first column,

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<sup>5</sup> Here, it was empirically difficult to distinguish whether it was second mover advantage or epidemic diffusion.

Table 3) showed that IT capital adoption behavior was different across lower and higher capital statements. Hospitals with a lower capital statement adopted less IT capital in response to neighbor hospitals' IT capital adoption. However, hospitals with a higher capital statement adopted more IT capital in response to neighbor hospitals' IT capital adoption and IT labor employment. Also, I only observed the substitution effect between neighbor hospitals' IT capital adoption and IT labor employment in hospitals with higher capital statements. An interesting finding was that IT capital adoption is negatively associated with labor expense in hospitals with lower capital statements.

[Table 3] System GMM Regression results across Capital Statement and Ownership

Variables	Capital Statement		Ownership		
	Lower 50%	Higher 50%	For-Profit	Not-for-Profit	Government
HHI	0.287 (0.349)	0.331 (0.505)	0.711* (0.393)	-0.172 (0.342)	0.699** (0.272)
% of Medicare patients	-0.290 (0.571)	-1.581** (0.634)	-2.083*** (0.432)	-0.139 (0.669)	-1.160** (0.513)
% of Medicaid patients	-1.763** (0.703)	-1.343** (0.567)	0.412 (0.582)	-0.474 (0.648)	-3.757*** (0.824)
Scale <sup>1</sup>	0.000 (0.000)	0.000 (0.000)	0 0.000	0 0.000	0.000*** 0.000
Scope <sup>2</sup>	-1.466* (0.867)	-0.192 (0.948)	-1.117 (1.460)	0.895* (0.461)	-8.397*** (1.425)
CMI	0.481 (0.369)	1.215*** (0.433)	2.081*** (0.366)	0.970** (0.383)	-1.539*** (0.497)
IT labor	-0.001 (0.018)	0.062 (0.048)	0.065 (0.047)	-0.03 (0.023)	0.006*** (0.074)
Capital Statement	0.222 (0.139)	0.207 (0.144)	0.198 (0.133)	0.267** (0.133)	0.272*** (0.092)
Labor Expense	-1.320** (0.324)	0.045 (0.227)	-0.034 (0.245)	-0.733** (0.304)	-1.450*** (0.268)
IT Capital Adoption of Neighbor	-1.102* (0.636)	1.312** (0.526)	-0.187 (0.893)	1.039*** (0.357)	1.480*** (0.413)
IT Labor Employment of Neighbor	-1.108 (0.710)	1.506** (0.626)	-0.121 (1.057)	1.064*** (0.411)	1.615*** (0.469)
IT Capital Adoption of Neighbor *	0.077*** (0.047)	-0.105*** (0.042)	0.001 (0.067)	-0.074*** (0.026)	-0.122*** (0.033)

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

1: Scale: the sum of outpatient visits and inpatient admissions.

2: Scope: number of outpatient visits over Scale.

Annual dummies included but not reported, ( ) represent standard error.

HHI, Herfindal-Herschman Index; CMI, case mix index.

### 5.1.2. Ownership

Hospitals have different goals across ownership type, i.e., profit maximization for for-profit hospitals and quality maximization for not-for-profit hospitals (Newhouse, 1970). Thus, the hospitals' different goals may influence their health IT adoption behavior as well. For example, if health IT could improve efficiency in terms of profit or cost, it would be an attractive incentive to for-profit hospitals. However, if health IT could improve quality, then it would be an attractive incentive for not-for-profit hospitals. For example, improved quality from health IT adoption could attract patients looking for better quality. Thus, ownership type may play a role in health IT capital adoption. To examine network effect across ownership types, hospital ownership was stratified as for-profit, not-for-profit and government hospitals, excluding federally-owned hospitals. The regression results (second column, Table 3) showed that neighbor hospitals' IT capital adoption and IT labor employment were associated with higher health IT capital adoption only in not-for-profit and government hospitals.

### 5.1.3. Teaching Status

Teaching status was designated by OSHPD and was defined as hospitals having teaching allowances and clinical teaching support. Teaching hospitals are often reported to be inefficient (Rosko, 2004; Koenig et al., 2005). Thus, they may have incentives to adopt health IT because IT could improve hospital efficiency by allowing them to share patient information. However, the regression results (first column, Table 4) showed that teaching hospitals did not respond to neighbor hospitals' IT capital adoption and IT labor employment.

### 5.1.4. Multi-hospital System Members

Hospitals within multi-hospital systems may behave differently from individual hospitals because of their specialized organizational relationships, such as consortia or contract management (Alexander and Mary, 1986). Thus, hospitals within multi-hospital systems may not respond to their neighbor hospitals' IT adoption behaviors. The regression results (second column, Table 4) showed that IT capital adoption of hospitals within multi-hospital systems was not associated with neighbor hospitals' IT capital adoption or IT labor employment. This result implies that the IT capital adoption decision making in these hospitals did not respond to other hospitals' behaviors. Only hospitals that were not a part of a multi-hospital system responded to their neighbor hospitals' behavior in IT adoption.

Overall, the regression results suggested that hospitals with higher capital statements, not-for-profit and government ownership, non-teaching and non-multi-hospital membership increased IT capital adoption in response to their neighbor hospitals' increase in IT capital adoption and IT labor employment.

**[Table 4]** System GMM Regression results across Teaching and Multi-hospital system member hospitals

Variables	Teach		Multihospital system	
	Non-Teaching	Teaching	Non-system	System
HHI	0.432 (0.451)	-0.405*** (0.150)	-0.112 (0.377)	0.672 (0.446)
% of Medicare patients	-1.376** (0.646)	0.038 (0.611)	-1.771** (0.778)	-0.863 (0.538)
% of Medicaid patients	-1.461** (0.742)	-0.798 (0.496)	-2.376*** (0.915)	-1.058** (0.515)
Scale <sup>1</sup>	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
Scope <sup>2</sup>	0.557 (0.977)	-6.368*** (1.000)	0.668 (0.754)	1.647 (1.261)
CMI	1.371*** (0.414)	-0.710*** (0.242)	0.330 (0.527)	1.212*** (0.308)
IT labor	-0.016 (0.027)	0.048** (0.019)	-0.003 (0.037)	0.042* (0.023)
Capital Statement	0.245* (0.128)	0.145* (0.079)	0.613*** (0.168)	0.023 (0.116)
Labor Expense	0.034 (0.261)	-0.704** (0.125)	-0.456* (0.273)	-0.422 (0.323)
IT Capital Adoption of Neighbor	1.017* (0.539)	0.074 (0.807)	0.889* (0.534)	0.374 (0.768)
IT Labor Employment of Neighbor	1.152* (0.612)	0.066 (0.901)	1.057* (0.587)	0.406 (0.869)
IT Capital Adoption of Neighbor *	-0.079**	-0.004	-0.075*	-0.027
IT Labor Employment of Neighbor	(0.040)	(0.058)	(0.041)	(0.056)

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

1: Scale: the sum of outpatient visits and inpatient admissions.

2: Scope: number of outpatient visits over Scale.

Annual dummies included but not reported, ( ) represent standard error.

HHI, Herfindal-Herschman Index; CMI, case mix index.

## VI. Discussion

This study examined the effect of neighbor hospitals' IT capital adoption and IT labor employment on a hospital's health IT capital adoption. This effect is important because U.S. hospitals have underinvested in health IT. This study used a novel data set from California hospitals; IT capital and IT labor dollar amounts were extracted from each hospital's balance sheet. As the results showed, neighbor hospitals' IT capital adoption and IT labor employment were found to play a crucial role in a hospital's health IT adoption. Overall, a hospital's IT adoption

behavior is interdependent with that of their neighbor hospitals. This implies that network externalities affect technology adoption directly, through interoperable technologies, and indirectly, through learning spillovers. For example, decision support systems in health ITs are more effective when they possess detailed information regarding patients' treatment histories and clinical characteristics. Thus, EMRs may exhibit network externalities as their value could increase if neighboring hospitals adopted interoperable EMRs (Lee et al., 2013).

This finding is generally consistent with research findings on epidemic learning or network effects (Karshenas and Stoneman, 1993) and with other hospital technology diffusion studies (Escarce, 1996; Berndt et al., 2003; Burke et al., 2007).

A substitution effect was found in between neighbor hospitals' IT capital adoption and IT labor employment and between a target hospitals' IT capital adoption and IT labor employment. Both of these findings may result from a labor shortage in this area. A recent survey by the College of Healthcare Information Management Executives (CHIME) revealed that 60 percent of hospital IT executives believe there is a shortage of IT workers. Moreover, according to the Bureau of Labor Statistics (2008), job opportunities for medical records and health information technicians are expected to grow by 20 percent through 2018, much faster than for other occupations. Thus, hospitals may need to pay a premium to hire IT workers because the amount of labor is limited. This lack of an IT labor workforce may deter the adoption of IT capital. However, this area needs further study.

These findings also suggest that, in general, competition was not associated with health IT capital adoption. This finding is generally consistent with other hospital's technology diffusion (Sloan et al., 1986; Romeo et al., 1984; Lee and Waldman, 1985; McCullough, 2008). Theoretically, competition plays a significant role in IT adoption, while empirically the health IT literature has reported mixed results (Capps and Cuellar, 2007; McCullough, 2008). However, the competition measure in this study may be correlated with other factors of cost and outcomes. In this case, this effect may be biased.

The regulation measured as Medicare population may negatively influence IT capital adoption. Higher coordination costs from a high proportion of Medicare patients may increase the return on investment of health IT adoption. Thus, a high proportion of Medicare patients may induce high health IT capital adoption. However, this regulation was not found to affect health IT capital in general.

Further, this network effect of IT varied across hospital characteristics. Hospitals' IT capital adoption was found to differ by level of capital statement. Hospitals with lower capital statements were responsive to neighbor hospitals' IT adoption because IT adoption may reduce cost and improve profit and quality. However, IT capital adoption is negatively associated with labor expense, indicating the hospitals are not on a high-enough level to adopt more IT capital to improve efficiency. Only the

hospitals with higher capital statements adopted more IT capital in response to neighbor hospitals' IT capital adoption and IT labor employment.

Hospital ownership plays an important role in IT capital adoption. Not-for-profit hospitals invest almost six times more in health IT capital than for-profit hospitals (\$8.5 million for not-for-profit vs. \$1.4 million for for-profit in the data set). Studies have reported that not-for-profit hospitals are more likely to adopt quality improving health IT such as EMR and CPOE (Lee et al., 2013). The quality improvements from health IT adoption are attractive to not-for-profit hospitals, which are trying to maximize quality of care. Thus, not-for-profit and government hospitals may increase IT capital spending in response to neighbor hospitals' IT capital adoption and IT labor employment. Results of this study also showed that the teaching hospitals did not respond to their neighbor hospitals' IT adoption behavior. As teaching hospitals are usually larger and inefficient hospitals, they may find it more difficult to respond to changes in their neighbor hospitals' behavior. Similarly, IT adoption in multi-hospital systems was not interdependent. Decision making for multi-hospital system members was more complicated compared to that for individual hospitals because multi-hospital systems have consortia or contract management among the members. Thus, they may not respond to changes in their neighbor hospitals' behavior. Overall, this study shows that health IT adoption behavior is interdependent among neighbor hospitals and varies across hospital characteristics.

## VII. Conclusion

As concerns of cost and quality of health care grow in hospitals, health IT has become increasingly important. In 2009, the Health Information Technology for Economic and Clinical Health (HITECH) Act was signed as a part of the American Reinvestment and Recovery Act (ARRA) to promote the adoption and meaningful use of health IT. HITECH allocated almost \$20 billion to subsidize the adoption of health IT and could potentially result in an IT subsidy of \$2 million to \$10 million per hospital. With this HITECH Act, hospitals are expected to increase health IT adoption. The increased health IT adoptions by hospitals, in turn, may lead to more IT adoptions by their neighbor hospitals, as this study showed. Thus, this increased IT investment will benefit hospitals by improving quality, outcome and efficiency and by reducing cost. There may be a need for strategic efforts to increase health IT adoption across hospital characteristics. As this study showed, hospitals' decisions on health IT adoption may be influenced by different hospital factors. For example, not-for-profit hospitals' IT adoption was affected by their neighbor's IT adoption behavior, whereas teaching and multi-hospital system member hospitals were not. Therefore, different strategies will be needed to

encourage health IT adoption by teaching hospitals and multi-hospital system member hospitals. These results provide insight into the health IT adoption process for government policy intervention to hasten the diffusion of health care IT adoption in hospitals.

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**[Appendix Table 1]** System GMM regression across median number of hospitals within 20 miles

Variables	Less than Median ( < 20)	Larger and equal to Median ( ≥ 20)
HHI	0.400 (0.393)	0.052 (0.432)
% of Medicare patients	-0.900 (0.550)	-0.867 (0.595)
% of Medicaid patients	-1.048 (0.695)	-1.191* (0.536)
Scale <sup>1</sup>	0.000 (0.000)	0.000 (0.000)
Scope <sup>2</sup>	-0.190 (0.513)	-0.004 (1.353)
CMI	1.372*** (0.376)	1.030** (0.421)
IT labor	-0.011 (0.028)	0.090*** (0.031)
Capital Statement	0.336*** (0.117)	0.158 (0.144)
Labor Expense	-0.876*** (0.198)	0.201 (0.282)
IT Capital Adoption of Neighbor	1.236*** (0.437)	3.830* (2.354)
IT Labor Employment of Neighbor	1.444*** (0.505)	4.596* (2.522)
IT Capital Adoption of Neighbor *	-0.096***	-0.299*
IT Labor Employment of Neighbor	(0.033)	(0.165)

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

1: Scale: the sum of outpatient visits and inpatient admissions.

2: Scope: number of outpatient visits over Scale.

Annual dummies included but not reported, ( ) represent standard error.

HHI, Herfindal-Herschman Index; CMI, case mix index.

**[Appendix Table 2]** System GMM regression after dropping the hospitals with the 10% lowest and 10% highest number of hospitals within 20 miles

Variables	System GMM
HHI	0.145 (0.392)
% of Medicare patients	-0.597 (0.564)
% of Medicaid patients	-0.995 (0.677)
Scale <sup>1</sup>	0.000 (0.000)
Scope <sup>2</sup>	1.279 (0.695)
CMI	0.235 (0.436)
IT labor	0.016 (0.026)
Capital Statement	0.280** (0.119)
Labor Expense	-0.452* (0.245)
IT Capital Adoption of Neighbor	1.441* (0.745)
IT Labor Employment of Neighbor	1.572* (0.838)
IT Capital Adoption of Neighbor *	-0.105*
IT Labor Employment of Neighbor	(0.055)

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

1: Scale: the sum of outpatient visits and inpatient admissions.

2: Scope: number of outpatient visits over Scale.

Annual dummies included but not reported, ( ) represent standard error.

HHI, Herfindal-Herschman Index; CMI, case mix index.