

Accepted Manuscript

Can Information Technology Help Hospital Employees to Reduce Costs?

Junsang Lee , Jinhyung Lee

PII: S2211-8837(18)30092-3
DOI: [10.1016/j.hlpt.2018.03.006](https://doi.org/10.1016/j.hlpt.2018.03.006)
Reference: HLPT 286



To appear in: *Health Policy and Technology*

Received date: 7 September 2017
Revised date: 27 February 2018
Accepted date: 25 March 2018

Please cite this article as: Junsang Lee , Jinhyung Lee , Can Information Technology Help Hospital Employees to Reduce Costs?, *Health Policy and Technology* (2018), doi: [10.1016/j.hlpt.2018.03.006](https://doi.org/10.1016/j.hlpt.2018.03.006)

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Highlights

- IT could be utilized to increase Case Mix Index (CMI)
- Only part time employees, not full time employees, are positively associated with CMI
- Negative association of IT and part time employees on CMI may imply that IT could help part time employees reduce CMI

ACCEPTED MANUSCRIPT

Can Information Technology Help Hospital Employees to Reduce Costs?

Junsang Lee, PhD

Department of Economics Sungkyunkwan University Seoul, Republic of Korea

822-760-0426

junsanglee@skku.edu

Jinhyung Lee, PhD

Department of Economics Sungkyunkwan University Seoul, Republic of Korea

822-760-0263

leejinh@skku.edu

Corresponding Author:

Jinhyung Lee, PhD

Department of Economics Sungkyunkwan University Seoul, Republic of Korea

822-760-0263

leejinh@skku.edu

Abstract

Objectives: The purpose of this study is to examine the association of hospital employees and health IT on Case Mix Index (CMI).

Methods: The California's hospitals observed for three consecutive years were included. Following a review of the available data, there were 180 hospitals selected from the surveys for three years from 2008 to 2010, for a total of 540 hospital observations. To examine the association of hospital employees and health IT on CMI, a generalized estimation equation (GEE) with log link and normal distribution was employed. Staffing (full-/part- time), hospital and market characteristics (hospital ownership, teaching status, network hospital status, competition and number of licensed beds), volume of hospital service (percentage of Medicare and Medicaid, total admissions, outpatient visits, emergency visits, and number of inpatient and outpatient surgeries) were controlled.

Results: It has three important findings. First, IT use was positively associated with CMI value. Second, the number of PTEs was positively associated with CMI value. Third, the interaction between IT and PTEs was negatively associated with CMI value.

Conclusions: The negative association between CMI value and the interaction of PTEs with IT cost implies that the use of IT systems may reduce some of the productive efforts of PTEs through DRG up-coding.

Keywords

Case Mix index; Full Time employees; Part Time employees; Health Information Technology

Introduction

Health information technology (IT) is designed to improve communications among providers within and among organizations by automating the collection, use, and storage of patient information. Thus, health IT can facilitate guideline compliance and decision support [1]. Moreover, previous studies have provided evidence that health IT can improve care quality by reducing errors and improving patient safety [2–9].

However, whether widespread use of health IT can lower healthcare costs remains unclear, as some studies have found that healthcare organizations may use health IT to receive higher reimbursements by selecting higher billing codes for certain diagnosis-related groups (DRGs) to reflect more intensive care administered, as part of a process known as DRG up-coding [10, 11].

To date, few studies have reported the presence of DRG up-coding associated with health IT system use. Li [10] examined the effects of electronic medical record (EMR) use on medical coding and billing in patient settings using longitudinal patient discharge data and found that the fraction of patients with higher DRGs was increased significantly after EMR adoption; specifically, the increased amount of reimbursement after EMR adoption was estimated to be US\$1.3 billion annually. Another study by Ganju et al. [11] considered the relationship between computerized physician order entry (CPOE) adoption and case mix index (CMI), which is a relative value assigned to individual patients' DRGs that is measured at the hospital level, and found that the adoption of CPOE systems was associated with an increase in CMI value corresponding to US\$300 million in inflated Medicare reimbursements per year. These studies suggest that health IT system use is positively associated with costs. Moreover, the United States Department of Health and

Human Services has argued that some providers are possibly using health IT systems to obtain payments for which they are not owed [12]. It has also been found that some hospitals may use health IT systems to facilitate the up-coding of the severity of patients' conditions without improving their quality of care [12].

Notably, however, these previous studies examined the effects of IT system use on cost without considering the relationship between hospital workers and IT. According to economics theory, firms try to maximize profits with technology, which has led them to invest in capital that both substitutes for workers and/or complements their skills. Generally, technology has replaced or aims to replace workers who perform routine tasks. Recently, complementary technologies have also been given to the very high-skilled workers. Healthcare is a service that is primarily provided by highly skilled workers [13]. However, the relationship between IT and these employees is not often considered in the healthcare setting. Still, though, it is a very important question to answer. For example, if an IT system is used as a substitute for employees or their skills, we need to find ways to make them better ready for this. On the other hand, if an IT system complements these employees, we could speed up the adoption of IT systems. Thus, the objective of this study was to examine the relationship between IT and hospital workers in explaining healthcare costs. In particular, this study focuses on the roles of part-time employees (PTEs). Because PTEs are considered to be temporary, in that they mostly replace or assist full-time employees (FTEs) for a specific period of time, their role in the hospital setting is different from that of FTEs. The primary reasoning for hiring PTEs is typically because of growth in work volume that exceeds the capacity of the available FTEs to handle. However, the increased capacity is not yet enough of an amount of work to justify the hiring of additional FTEs. Nearly 32 million PTEs are employed in nonagricultural industries in the United States currently. Moreover, the percentage of PTEs in the California healthcare field is more than 25% of total workers [14].

Thus, differently from previous studies, this study considered the relationship between IT and hospital workers in explaining CMI, focusing on the different effects of PTEs and FTEs using California hospital data from 2008 to 2010.

Data Source

Hospital financial data from California's Office of Statewide Health Planning and Development (OSHPD) and an annual survey of hospitals provided by the American Hospital Association (AHA) were used in this study. The OSHPD collects and publicly discloses facility-level data from more than 6,000 licensed healthcare facilities including hospitals, long-term care facilities, clinics, home health agencies, and hospices. As part of this, California hospitals are required to submit a Hospital Annual Disclosure Report within four months of the hospital's fiscal year end. The report contains various pieces of information such as type of ownership and inventory of provided services, number of beds and corresponding utilization patient statistics by payer, balance sheet and income statement, revenues by payer and revenue center, expenses by natural classification and cost center, and productive hours and average hourly rates by employee classification and cost center [15]. The AHA data provide detailed state-wide hospital information. The AHA annual hospital survey profiles more than 6,500 hospitals throughout the United States. The response rate on the AHA annual hospital survey has been more than 70% each year it has been administered. The survey process is conducted to maximize accuracy and participation¹. The AHA data are used by government agencies, media, and the healthcare industry for accurate and timely analysis and decision-making. The database contains hospital-specific data on hospitals and healthcare systems (except federal government hospitals), including organization location, size, structure and personnel [16]. These data have been used in many healthcare and economic studies [17, 18].

In the current study, only California's hospitals observed for three consecutive years were included. Following a review of the available data, there were 180 hospitals selected from the surveys for three years from 2008 to 2010, for a total of 540 hospital observations.

Dependent Variables

The CMI is a relative value assigned to a patient's DRG in a medical care environment. The value of CMI is applied to determine the resources allocated to take care of patients in a specific group. It represents the clinical complexity and diversity of the patient population in a given hospital [14]. To calculate CMI value, each patient is

¹See detailed process at <http://www.ahadataviewer.com/about/data/>.

assigned to one of more than 700 Medicare Severity-Diagnosis Related Groups (MS-DRGs) based on their principal and secondary diagnoses, age, procedures performed, presence of co-morbidities or complications, discharge status, and gender. Each MS-DRG has a numeric weight that represents the national average hospital resource consumption by patients in that group relative to all patients. The CMI value is then calculated by averaging the MS-DRG weight of patients discharged within the same calendar year [14]. A higher CMI value indicates a more severe MS-DRG coding of a patient.

Independent Variables

The following three groups of independent variables were controlled: employees, hospital and market characteristics, and volume of hospital service. Employees were grouped as FTEs and PTEs. The FTEs were defined as people who worked more than 35 hours per week, including physicians, dentists, medical and dental residents and interns, other trainees, registered nurses, licensed practical or vocational nurses, nursing assistive personnel, radiology technicians, laboratory technicians, pharmacists, licensed, pharmacy technicians, respiratory therapists, and other personnel. The PTEs were defined as the same, except that they worked less than 35 hours per week on the hospital/facility payroll. Hospital and market characteristics included ownership, teaching status, network hospital status, competition, and number of licensed beds. Hospital ownership was categorized into three groups: for-profit, not-for-profit, and government. They were measured with two dummy variables, with for-profit hospitals serving as the reference. Teaching status was a dummy variable indicating whether the hospital was a teaching hospital and was defined by membership in the Council of Teaching Hospitals (COHA) of the Association of American Medical Colleges. The number of licensed beds was defined as the total number of beds authorized by the state licensing agency. Network hospitals were defined as those with system membership and represented by a dummy variable. To measure the competition of a given geographical market based on health service area (HSA), a hospital's adjusted admissions were calculated based on its total number of admissions and outpatient visits [18]. The share of adjusted admissions for a hospital within each HSA was then calculated. Lastly, this share of adjusted admissions was squared and summed across HSA to generate a Herfindahl-Hirschman Index (HHI) value, an economic concept widely

used to measure competition [17-18]. The volume of hospital service included the percentage of Medicare and Medicaid admissions out of the total number of admissions as well as the total number of admissions, outpatient visits, emergency room visits, and the number of inpatient and outpatient surgeries.

As a key explanatory variable, health IT use was measured in US dollar amount for both capital and labor related to IT. OSHPD data placed all IT expenditures within the data processing section of financial statements. Health IT capital (i.e., physical capital, purchased services, leases/rentals, and other direct expenditures) and IT labor (i.e., salaries and wages, employee benefits, and professional fees) were measured in US dollars and extracted from each hospital's balance sheet [18].

Statistical Analysis

To examine the effects of hospital employee and IT cost on CMI value, a generalized estimation equation (GEE) with log link and normal distribution was employed. This estimation approach has been used in many prior research efforts, focusing on population-averaged estimates that indicate the effect of regression average over the population of subjects [19-21]. The GEE is able to control variance structure and clustering error with regard to hospitals. For model selection, quasi-likelihood under the independence model criterion (QIC) was tested and independent variance model with the smallest QIC was chosen among the many possible variance structures [22]. In the GEE model, employees (FTEs/PTEs), hospital and market characteristics (e.g., hospital ownership, teaching status, network hospital status, competition and number of licensed beds), and volume of hospital service (i.e., percentage of Medicare and Medicaid admissions, total admissions, outpatient visits, emergency visits, and number of inpatient and outpatient surgeries) were included with IT cost. The years were dummy variables from 2008 to 2010. All of the analyses were conducted using Stata 11.2 [23].

RESULTS

Descriptive Statistics

Data of descriptive statistics for variables used are shown in Table 1. The first row shows CMI value, employee type, and IT cost. The average CMI value was 1.184. The average number of FTEs was 1,200, while that of PTEs was 422. The average IT cost was more than US\$14 million. The second row of Table 1 shows hospital characteristics. Not-for-profit hospitals accounted for almost 60% of those considered, while for-profit and government hospitals each accounted for 20%. Teaching and network hospitals accounted for 7.6% and 20.6%, respectively. Competition measured as HHI was 64.4%. The average number of licensed beds was 270. The last row of Table 1 shows hospital volume. There were 11,425 average total admissions and 172,410 average outpatient visits. The percentage of Medicare admissions out of the total number of admissions was 45.5%, while that of Medicaid admissions out of the total number of admissions was 25%. The total number of emergency room visits was more than three times larger than that of total admissions. There were 3,051 and 3,995 inpatient and outpatient operations performed, respectively.

Statistical Results

To check multicollinearity, variance inflation factor (VIF) was examined. As a general rule, a variable with a VIF value exceeding 10 may require further investigation [24]. However, all VIF values in this study were less than 10. The top three VIF values were 8.21 for total FTEs, 8.20 for total admission, and 6.50 for licensed beds.

As shown in Table 2, IT cost was positively associated with CMI value. For example, about a 1% increase in CMI value was observed when IT cost was increased by 10%. This is consistent with the findings of previous studies [10, 11]. Second, the number of PTEs was positively associated with CMI value. For example, if we increase the number of PTEs by 10%, we can expect the CMI value to increase by 33%. A higher CMI value indicates that the hospital performs more “big-ticket” services. Therefore, more money per patient is received. Third, the interaction between PTEs and IT was negatively associated with CMI value. For example, about a 0.2% decrease in CMI value was observed when IT and the number of PTEs were increased by 10%. The negative association between CMI value and the interaction of PTEs with IT cost implies that the use of IT systems may reduce some of the productive efforts of PTEs through DRG up-coding. However, the

number of FTEs and the interaction of FTEs with IT cost were not statistically significant, meaning neither variables were associated with CMI value.

However, there might be reverse causality between independent variables (FTEs, PTEs, and IT) and CMI value because a higher CMI value might indicate that larger hospitals require more FTEs and PTEs and increased IT capabilities. Thus, the relationship between CMI value and one time lagged or forward terms of FTEs, PTEs, and IT was tested. As shown in Table 3, only lagged terms, not forward terms, of FTEs, PTEs, and IT were significant². This implies that hospitals with higher CMI values may not need more FTEs, PTEs, or greater IT capabilities.

The measure of employees included all clinical and non-clinical employees. However, only clinical employees might have access to the IT system related to DRG coding. Thus, clinical employees were separated from the non-clinical ones. Moreover, clinical employees were grouped into full- and part-time clinical employees. Full-time clinical employees were defined as FTEs excluding other personnel (e.g., those with administrator or clerical functions), while part-time clinical employees were defined as PTEs excluding other personnel. Non-clinical staff members included all other personnel. As shown in Table 4, only part-time clinical employees were positively associated with CMI value. In addition, the interaction between part-time clinical employees and IT was negatively associated with CMI value. This finding confirmed the first regression result—that is, that IT use could reduce the efforts of PTEs.

We also found that hospital characteristics were important factors in CMI. Government hospitals had lower CMI values than did for-profit hospitals. However, hospitals with teaching status, a larger number of licensed beds, and network inclusion had higher CMI values. The percentage of Medicare admissions and the number of inpatient surgery procedures were also positively associated with CMI value, although the total number of admissions and the number of outpatient visits were negatively associated with CMI value.

Discussion

²The coefficient of PTEs is marginally significant at 10% p-value, while those of FTEs or IT cost are not.

CMI is a very important indication that hospitals should track. For example, a drop in CMI value at a particular hospital could be a sign that the hospital is not capturing complications or comorbidities grouped into higher-weighted DRGs [25]. Thus, to select higher billing codes or higher CMI values, IT was utilized [10-11]. However, previous studies have focused on the relationship between IT and CMI without considering the employees handling the IT system. Thus, we considered the relationship between IT and employees in explaining CMI, focusing on the different effect of PTEs and FTEs. From this study, we had the following three major findings. First, IT could be used to increase CMI value after controlling for hospital and market characteristics and volumes. This confirmed the argument of some vendors that healthcare organizations are getting more money with IT adoption because patient diagnosis coding can be easily modified. This result is in agreement with previous findings [10, 11] showing that health IT systems use is associated with higher billing amounts.

Second, this study found that only the number of PTEs was positively associated with CMI, implying that these individuals might see more severe patients. This result is consistent with the results of a previous study [26] that indicated that PTEs demonstrate more productivity versus FTEs. For example, Fairchild et al. [26] found that productivity as measured by relative value units (RVUs) per clinical hour is significantly higher for part-time primary care physicians (PCPs) as compared with that of full-time PCPs with similar rates of patient satisfaction, compliance with screening guidelines, and resource use. Specifically, the productivity of part-time PCPs was found to be greater than that of full-time PCPs by 0.8 work RVUs per clinical hour. This might be due to their association with higher CMI values. However, previous studies have also found that FTEs may wish not to participate in the activities of low physician RVUs per amount of time involved, while PTEs may more readily choose to be involved with activities with low RVUs [26]. Other studies have also suggested that PTEs are concerned about their role in less desirable work assignments and have proportionally greater workloads³ than those of their full-time colleagues [27, 28]. Thus, PTEs may not see more severe patients. However, they may still claim higher coding values than expected by using the IT system.

³In this study, CMI was not related to volume because CMI was defined by averaging the MS-DRG weight of patients discharged within a certain calendar year.

Third, the negative interaction of IT and PTEs in CMI may imply that IT could prevent CMI from being inflated by PTEs. PTEs may be unwilling to participate in work initiatives that occur during times beyond regular work hours, such as committee work, leadership efforts, marketing, the development of new procedures and study protocols, and quality improvement activities. In term of patient quality of care, they might have more difficulty with providing continuity in certain ongoing cases. This may lead to higher DRGs. However, PTEs may improve their work efficiency or reduce unnecessary care by using IT to improve the continuity of care by providing patient information, resulting in cost savings. However, FTEs and the interaction of FTEs and IT were not associated with CMI value. This result implies that IT systems may not help or complement the work of FTEs, which is different from the case with PTEs.

Hospital characteristics also played a significant role. Among the ownership types, the for-profit hospitals had higher CMI values than did government hospitals. This finding is also consistent with those of other studies. Generally, for-profit hospitals are keen to generate profits, which may result from higher CMI values [10]. Teaching hospitals had higher CMI values because teaching hospitals may serve as referral centers for patients with severe diseases [29]. Additionally, network hospitals had higher CMI values. These institutions may manage tougher cases or better medical records systems [30]. Hospital with larger bed numbers also had higher CMI values. Among the volume variables, the percentage of Medicare admissions and inpatient surgery procedures were positively associated with CMI value. Medicare patients are those who are older than 65 years of age and who may have more severe or chronic disease. Inpatient operations also need more resources to treat patients as compared with outpatient procedures. Total admissions and outpatient visits were negatively associated with CMI value.

There are some limitations to consider when interpreting our findings. The first limitation pertains to the limited external validity of this study, as we used data only from hospitals in California. We are, therefore, unable to generalize our findings to other states or countries, especially those with different patterns of employee and financing systems. Second, while IT cost was broadly defined as US dollars invested in both capital and labor related to IT, certain costs of health IT, like backfill time for IT personnel, management, or

workflow redesign, could not be measured. Third, the associations we investigated are likely affected by the baseline status of health IT; however, we could not access these data. Thus, this potential effect of IT and the interaction of IT and employees on CMI value may change over time within those systems. Lastly, there may be unobserved confounding factors that might impact our estimates; for example, organizational and management behaviors may be correlated with IT cost [6].

We focused on the hospital-level data in this study. Thus, we cannot observe any effect of IT and the interaction between IT and employees on specific disease categories. There may be more manageable disease categories for DRG up-coding, but they may require more sophisticated measures for detection.

Conclusion

To the best of our knowledge, this study is the first study to examine the interaction between employees and IT system use in a hospital setting. It has three important findings. First, IT use was positively associated with CMI value. Second, the number of PTEs was positively associated with CMI value. Third, the interaction between IT and PTEs was negatively associated with CMI value.

This study has important policy implications. Policymakers, researchers, and health professionals should be cautious when interpreting these results and should remember that IT adoption could lead to higher patient costs. Thus, ways to prevent up-coding with health IT system use should be considered. For example, we could monitor and audit EMR systems on the payer side and regulate the way vendors design their EMR products. Also, health IT systems could complement the work done by the PTEs to decrease CMI value or costs, which may reduce unnecessary care or resources. Thus, we could speed up adopting health IT systems despite the barriers for adopting them that have been reported, which include workflow disruption, communication among users, complexity, need for physical space, and resistance from physicians [31, 32]. Overall, the findings of this study are expected to aid managers of healthcare organizations in adopting health IT systems for employee use in a way that is beneficial for both the patient and the institution.

Acknowledgement

Funding: None

Competing interests: None declared

Ethical approval: Not required

ACCEPTED MANUSCRIPT

<Reference>

- [1]. Institute of Medicine: Crossing the quality chasm: a new health system for the 21st century. 2001, National Academies Press, Washington (DC)
- [2]. Kuperman G, Gibson R: CPOE: benefits, costs, and issues. *Ann Intern Med.* 2003, 139 (1): 31-39.
- [3]. Garg A, Adhikari N, McDonald H, et al: Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: a systematic review. *JAMA.* 2005, 293 (10): 1223-1238.
- [4]. Chaudhry B, Wang J, Wu S, et al: Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. *Ann Intern Med.* 2006, 144 (10): 742-752.
- [5]. Parente S, Horn RV: Valuing hospital investment in information technology: Does government make a difference?. *Health Care Financ Rev.* 2007, 28 (2): 31-43.
- [6]. Borzekowski R: Measuring the cost impact of hospital information systems: 1987–1994. *J Health Econ.* 2009, 28: 938-949.
- [7]. Parente S, McCullough J: Health information technology and patient safety: Evidence from panel data. *Health Aff.* 2009, 28: 357-360.
- [8]. Yu FB, Menachemi N, Berner ES, et al: Full implementation of computerized physician order entry and medication-related quality outcomes: a study of 3,364 hospitals. *Am J Med Qual.* 2009, 24 (4): 278-286.
- [9]. Himmelstein DU, Wright A, Woolhandler S: Hospital computing and the costs and quality of care: a national study. *Am J Med.* 2010, 123 (1): 40-46.
- [10]. Li, B. Cracking the codes: do electronic medical records facilitate hospital revenue enhancement. 2014, Working paper.
- [11]. Ganju, Kartik K. and Atasoy, Hilal and Pavlou, Paul A., Do Electronic Medical Record Systems Inflate Medicare Reimbursements?, 2016, Fox School of Business Research Paper No. 16-008.
- [12]. IMPACT: Cabinet officials signal crackdown on Medicare billing abuse, <https://www.publicintegrity.org/2012/09/24/10971/impact-cabinet-officials-signal-crackdown-medicare-billing-abuse>
- [13]. Hicks M., Technology Both Complements and Substitutes for Labor, 2016, <http://www.innovativeworkforce.com/technology-both-complements-and-substitutes-for-labor/>
- [14]. Office of States Wide Health Planning and Development (OSHPD), Case Mix Index <https://www.oshpd.ca.gov/HID/Products/PatDischargeData/CaseMixIndex/>

- [15]. Office of States Wide Health Planning and Development (OSHPD), Data and Reports, <https://www.oshpd.ca.gov/HID/>
- [16]. American Hospital Association Data and Directories. 2012. <http://www.aha.org/research/rc/stat-studies/data-and-directories.shtml>.
- [17]. Lee J., Impact of hospitalist care on hospital malpractice premiums using California hospital data, *Applied Economics Letters*, 2016, 24(11): 742-752
- [18]. Lee J., McCullough JS, Town RJ, The impact of health information technology on hospital productivity, 2013, *The RAND Journal of Economics*. 44(3): 545-568
- [19]. Gibbons RD, Hedeker D, DuToit s, *Advances in Analysis of Longitudinal Data, Annu Rev Clin Psychol*.2010, 26(6): 79-107
- [20]. Wang Ming, *Generalized Estimating Equations in Longitudinal Data Analysis: A Review and Recent Developments, Advances in Statistics*, 2014, 303728,: 1-11
- [21]. Lee J., JY Choi, Texas hospitals with higher health information technology expenditures have higher revenue: A longitudinal data analysis using a generalized estimating equation model, *BMC health services research*, 2016
- [22]. Cui J. QIC program and model selection in GEE Analyses, *The Stata Journal*. 2007: 7(2), 209-220
- [23]. StataCorp. *Stata Statistical Software: Release 14*. 2015, College Station, TX: StataCorp LP.
- [24]. Williams R., *Multicollinearity*, 2015, University of Notre Dame, <http://www3.nd.edu/~rwilliam/>
- [25]. HCPro, 2010, <http://www.hcpro.com/HOM-250674-5728/What-does-casemix-index-mean-to-you.html>)
- [26]. Fairchild DG, McLoughlin KS, Gharib S, et al., Productivity, quality, and patient satisfaction: comparison of part-time and full-time primary care physicians. *J Gen Intern Med*. 2001: 16(10):663-7
- [27]. Harrison R, Gregg J. A time for change: an exploration of attitudes toward part-time work in academia among women internists and their division chiefs. *Acad Med* 2009;84:80-6.
- [28]. Bunton S, Corrice A. An exploration of part-time U.S. medical school faculty: a thematic overview. Available at: <https://members.aamc.org/eweb/upload/An%20Exploration%20of%20Parttime%20US%20Medical%20School%20Faculty.pdf>.
- [29]. Mendez CM, Harrington DW, Christenson P, Spellberg B., Impact of Hospital Variables on Case Mix Index as a Marker of Disease Severity, *Population Health Management*, 2014, 17(1)

- [30]. Watt, J. Michael, Steven C. Renn, James S. Hahn, Robert A. Derzon, and Carl J. Schramm. *The Effects of Ownership and Multihospital System Membership on Hospital Functional Strategies and Economic Performance*. Washington (DC): National Academies Press (US); 1986.
- [31]. Burke DE, Wang BB, Wan TT, Diana ML. Exploring hospitals' adoption of information technology. *J Med Syst*. 2002;26(4):349–55.
- [32]. Ajami S, Bagheri-Tadi T. Barriers for Adopting Electronic Health Records (EHRs) by Physicians. *Acta Inform Medica*. 2013;21(2):129–34.

ACCEPTED MANUSCRIPT

Table 1. Descriptive Statistics

Variables	Description	Mean	Std. Dev.
Case Mix Index		1.184	0.232
Empoyees	All	1,622	1,577
	Full time	1,200	1,327
	Part time	422	402
IT		14,681,347	31,246,201
Characteristics	Ownership	Profit	19.4%
		NFP	58.9%
		Government	21.7%
	Teaching Hospital	7.6%	
	Network	20.6%	
	Competition	64.4%	
	Licensed Beds	270	184
	Volume	% Medicare	45.5%
% Medicaid		25.0%	
Total Admissions		11,425	8,492
Outpatient Visits		172,410	182,634
ER Visits		36,069	23,569
Surgery Inpatient		3,051	2,699
Surgery Outpatient		3,995	3,146

Table 2. GEE regression Results of Full/Part time employees

Variables		Coefficients	(S.D.)
Employees	Full time	-0.095	0.130
	Part time	0.331**	0.139
IT		0.102**	0.045
IT * Full time		0.007	0.008
IT * Part time		-0.018**	0.009
Ownership	NFP	-0.025	0.020
	Government	-0.050*	0.026
Teaching Hospital		0.128***	0.031
Network		0.042***	0.015
Competition		-0.002	0.016
Licensed Beds		0.096***	0.021
% Medicare		0.444***	0.096
% Medicaid		0.004	0.081
Total Admissions		-0.135***	0.021
Outpatient Visits		-0.024*	0.013
ER Visits		-0.008	0.006
Surgery Inpatient		0.077***	0.018
Surgery Outpatient		0.013	0.011
Const.		-1.668**	0.662

*** p<0.01, ** p<0.05, * p<0.1

Year dummies were included in regression, but are not shown in the table

Table 3: GEE regression Results lagged and forward variables

Variables		One time lagged (t-1)		One time forward (t+1)	
		Coefficients	(S.D.)	Coefficients	(S.D.)
Employees	FTE	-0.233	0.161	-0.102	0.155
	PTE	0.549***	0.178	0.287	0.158*
IT		0.129**	0.055	0.084	0.054
IT *	FTE	0.016	0.010	0.008	0.009
IT *	PTE	-0.031***	0.011	-0.015	0.010

* p<0.01, ** p<0.05, * p<0.1

Hospital Characteristics and Volumes were controlled, but not shown in the table.

The regression coefficients of Hospital Characteristics and Volumes were similar with table 2.

Table 4: GEE regression Results clinical full/part and non-clinical staffing.

Variables		Coefficients	(S.D.)
Clinical Staffing	Full time	-0.220	0.218
	Part time	0.283***	0.084
Non-Clinical Staffing	All	0.210	0.267
IT Cost		0.117***	0.043
IT cost*	Clinical FTE	0.015	0.013
IT cost*	Clinical Part	-0.016***	0.005
IT cost*	Non-Clinical Staffing	-0.012	0.016

* $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Hospital Characteristics and Volumes were controlled, but not shown in the table.

The regression coefficients of Hospital Characteristics and Volumes were similar with table 2.