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RESEARCH ARTICLE

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Does IT Improve Revenue Management in Hospitals?

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Abstract

In this study, we examine the question of how the adoption of IT systems influences revenue management in hospitals. We posit that IT plays a vital role in enhancing revenue by increasing net patient revenue and decreasing the uncompensated care ratio. Using unique datasets from various proprietary resources, we test the relationships between IT (clinical and business) investment and revenue management performance using dynamic panel data models with the generalized method of moments (GMM). Empirical results generally support our hypotheses. We found that both clinical and business IT investment have short-term and long-term effects on boosting net patient revenue and that clinical IT investment has a short-term contemporaneous effect on reducing the uncompensated care ratio. Moderation analyses suggest that: (1) larger hospitals tend to utilize business IT systems better in facilitating revenue management through both channels over the long run, but not necessarily using clinical IT; and (2) for-profit hospitals outperform their nonprofit counterparts when it comes to managing revenues through clinical IT; however, no interaction effect with business IT was found. This paper contributes to the literatures on the business value of IT investment and healthcare IT in the fields of information systems, revenue management, healthcare administration. We conclude this paper by discussing theoretical and managerial implications.

Keywords: IT, Hospital, Clinical, Business, Revenue Management, Patient Revenue, Uncompensated Care, Nonprofit, For-Profit, HIMSS, OSHPD

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1 Introduction

The information technology (IT) and healthcare literatures have clearly documented that IT can enhance operational and financial performance (Barua & Mukhopadhyay, 2000; Setia et al., 2011; Tanriverdi, 2006). For healthcare organizations, IT has long been viewed as an important lever to improve financial and operational viability. According to a McKinsey & Company report by Laflamme, Pietraszek, and Rajadhyax (2010), US hospitals will spend approximately $120 billion, at an average cost of $80,000 to $100,000 per bed, on IT in the upcoming years, highlighting the significance of these investments for the health care industry. Investments in IT, for example, can increase hospital productivity (Menon, Lee, & Eldenburg, 2000), reduce operating costs (Glaser, Drazen, & Cohen, 1986; Hillestad et al., 2005), increase quality of care (Chaudhry et al., 2006; McCullough, Casey, Moscovice, & Prasad, 2010) and reduce information asymmetries between consumers and providers through improved voluntary disclosures (Angst et al., 2014). More recent studies examine the role of IT on other aspects of the healthcare quality and hospital performance, including the studies by

Yaraghwe (2015) and Eftekhari et al. (2017) on the effect of health information exchanges on reducing repetitive medical tests and services and a study that investigates the spillover effects of health IT investments on regional healthcare costs (Atasoy, Chen, & Ganju, 2017).

While considerable research has examined the effect of IT in healthcare organizations, the focus has been on operating cost, quality, and quantity. The impact of IT on the revenue side of the performance equation has been understudied. Just as firms manage costs, whether through actual productivity gains or by strategically managing reported cost via real earnings management (Eldenburg et al., 2011), research also acknowledges that firms manage revenues. Considerable extant literature has explored mechanisms through which organizations manage their revenues (McGill & van Ryzin, 1999; Talluri & van Ryzin, 2005). In extreme cases, firms might also engage in improper activities such as recognizing fictitious revenues, overbilling, kickbacks, or channel stuffing to manage their revenues (Dechow, Ge, & Schrand, 2010; Stubben, 2010). While firms operating in other industries can simply drop unprofitable product lines or strategically allocate resources to high-margin items, this flexibility is not available in the hospital industry because of two factors: health care regulation and the predominantly nonprofit structure of the industry. Health care in the US is subject to a complex and oftentimes bewildering array of regulations that largely shape organizations' choices with respect to managing their costs and revenues. On the cost side, hospitals face multiple demands to provide costly services that are either not reimbursed (such as care for the indigent population) or underreimbursed (e.g., some services provided to fee-regulated patients such as Medicaid patients). Recent data from the American Hospital Association's (AHA) Annual Survey of Hospitals shows that US hospitals provided $38.3 billion in uncompensated care in 2016, up from $35.7 billion in 2015, which does not even include underpayment from Medicare or Medicaid.[1] On the revenue side, hospitals' pricing options are largely regulated. For instance, most patients admitted to a hospital are covered by insurance plans that either reimburse hospitals based on a flat rate per diagnosis (e.g., Medicare or Medicaid programs) or a fee-capped scheme (e.g. HMOs or PPOs). Therefore, hospitals have limited flexibility in influencing revenues through increased mark-up or premium pricing. In addition, public insurance programs such as Medicare and Medicaid are, respectively, federally funded or state supported. Within Medicare, which is reimbursed on a flat-fee, there are some portions that are traditional indemnity-based plans and others that are managed-care-based plans. Medicaid reimbursement rates are not only lower than Medicare rates (about 66% of Medicare rates for the US) but are subject to the vagaries of state budgets, priorities, and politics. Further, while for-profit hospitals can turn nonemergency patients away, nonprofit hospitals are not allowed to turn away patients, regardless of their insurance status. The US hospital industry is primarily comprised of nonprofit hospitals, which have a market share of 87% of the total community hospital beds (cdc.gov). This situation poses a quandary to hospitals—on the one hand, they seek to maximize a multidimensional objective function that includes providing unprofitable services, subject to a breakeven profit constraint in the case of nonprofits, or a profit constraint in the case of for-profits. On the other hand, these unprofitable services must be either self-sustaining or supported by transitory revenue sources such as donations and subsidies.

Revenue management provides a powerful tool for hospitals to continue providing unprofitable services, consistent with their objective function. Since researchers have found that IT can enhance multiple aspects of hospital performance, we are also interested in exploring the role of IT systems in hospitals' revenue management, which will contribute to the information systems and healthcare administration literatures. By "revenue management," we imply both enhancing revenue generation and improving the efficiency of the revenue cycle to reduce the amount of uncompensated care. We argue that, overall, IT (both clinical and business) systems can improve the efficiency of clinical and nonclinical processes in hospitals and therefore help them manage uncompensated care issues. Also, we suggest that it takes time for IT adoptions to be completely assimilated and IT systems to be fully understood and utilized by physicians, nurses, and administrators in hospitals. Therefore, IT investments have long-term effects in addition to their short-term effects. Finally, we explore the heterogeneous effects of IT on revenue management performance across different hospital types because hospitals with different missions might not equally value revenue management and may use IT in different ways.

We combine two unique secondary data sources on hospitals' IT adoption and financial information and conduct empirical analyses to examine the relationships between clinical and business IT investments and two aspects of revenue management. Our empirical results can be summarized as follows. First, found that both clinical and business IT

[1] "Hospital Uncompensated Care Costs Climb in 2016" (https://www.aha.org/news/headline/2018-01-04-hospital-uncompensated-care-costs-climb-2016).

investment have positive short-term and long-term effects on enhancing net patient revenue. In other words, investment in both types of IT systems helps bring in more revenue both in the same year and within several years of adoption. Second, clinical IT investment was found to have a short-term effect on reducing the uncompensated care ratio. Even though we did not find the effect of business IT on the reduction of uncompensated care rate in our main analyses, we found that larger hospitals tend to utilize business IT systems better in facilitating revenue management through this channel over the long run, partly because of the fact that larger organizations have better resources to support and complement IT adoptions. Additional moderation analyses further suggest that nonprofit hospitals, compared to their for-profit counterparts, do not perform as well when it comes to managing revenues with the help of clinical IT, probably because of the lack of incentives to maximize revenue and minimize bad debt. However, we found no interaction effect between nonprofit status and business IT investment.

The rest of the paper is organized as follows: Section 2 discusses the theoretical background of our study, including the role of IT in organization performance and the significance of revenue management, and provides a review of prior studies in these fields. In Section 3, we develop hypotheses on the effect of IT on two revenue management measures and their moderating effects according to hospital size and type. Section 4 presents our methodology description, including an explanation of variables and econometric specifications. In Section 5, we present the empirical results on those hypothesized relationships. Section 6 summarizes and concludes the paper by discussing both academic contributions and managerial implications.

2 Theoretical Background

2.1 IT and Organizational Performance

The literature on IT and organizational performance is rich with both theoretical conceptualization and empirical testing. Bharadwaj (2000) and Melville, Kraemer, and Gurbaxani (2004) use the resource-based view to explain why IT creates value for organizations. Sambamurthy, Bharadwaj, and Grover's (2003) conceptualization of the role of IT in contemporary firms discusses how digital options shape organizational agility. Empirically, earlier work in the field of information systems, such as Weill's study (1992), investigates the impact of IT investment in the manufacturing sector and Bharadwaj, Bharadwaj, and Konsynski (1999) provide evidence supporting the relationship between IT investment and firm performance measured using Tobin's q. Ray, Muhanna, and Barney (2005) look at the firm performance in terms of customer service, and Rai, Patnayakuni, and Seth (2006) examine the firm performance impacts of digitally enabled supply chain systems. More recent work, such as Tambe & Hitt's studies (2012, 2013), provide further evidence using alternative measures of IT and firm performance. These studies indicate that the performance impacts of IT applications vary across different categories of applications (Setia et al., 2011). In the health IT literature, Barua and Mukhopadhyay (2000), Tanriverdi (2006), and Setia et al. (2011) examine the performance implication of IT in the healthcare sector. While most prior work focuses on cost and quality, this study contributes to the literature by examining the effect of IT on hospitals' revenue enhancement performance and the underlying mechanisms of bad-debt management.

Like many researchers in previous studies, we use the resource-based view as the theoretical foundation to explain why IT creates value for hospitals. The resource-based view posits that firms differ in their possession of resources, some of which are rare, inimitable, and tied semipermanently to the firm; if used effectively, the resource-based view suggests that this resource asymmetry can serve as a source of sustained competitive advantage (Amit & Schoemaker, 1993; Barney, 1991, 2001). The resource-based view considers a broader set of resources, capabilities, and competencies, including in-house knowledge, technical capabilities, and management skills (Mahoney & Pandian, 1992; Penrose, 1959; Wernerfelt, 1984). IT is one of those resources and is valuable for organizations if it is rare, unique, and imitable. Adopting IT systems creates competitive advantages for businesses, especially for early adopters. IT systems adopted by general businesses can be further categorized according to several types, such as data processing, e-commerce, telecommunication, and decision support, among others. Prior research has predominantly focused on the impact of adoption and use of a certain technology or the dollar amount of investments on IT; while such studies are valuable, a focus on the entire portfolio of IT provides a more nuanced view (Mendelson, 2000; Setia et al., 2011). Whereas Setia et al. (2011) offer constructs of IT-application architecture spread and IT application architecture longevity, we create similar portfolio-based variables to measure IT adoption. In making IT investment decisions, hospitals face numerous challenges. First, there is a plethora of health information technologies and hospitals must assess which of these technologies are appropriate for their specific needs. Hospital IT systems can be classified into two broad categories: (1) business IT systems such as patient billing, credit and collection systems, and scheduling systems that help enhance revenues and effectively utilize capacity (Elkhuizen et al., 2007), and (2) clinical IT systems such as cardiology information systems, pharmacy management systems, and laboratory IS that are used to assist medical providers in patient treatment and improve health outcomes (Robinson & Luft, 1988). In this paper, we explore the depth of both business and clinical IT systems.

2.2 Revenue Management

In the non-healthcare context, previous studies have documented various mechanisms through which organizations strategically manage their revenues, such as pricing, product mix, customer mix, markets coverage, and market segmentation decisions (McGill & Van Ryzin, 1999; Talluri & Van Ryzin, 2005). For example, McGill and Van Ryzin (1999) discuss revenue management practices in the airline industry including forecasting, overbooking, seat inventory control, and pricing in relation to their impacts on airlines' revenue enhancement. In a more comprehensive tutorial in operations research, Talluri and Van Ryzin (2005) introduce the concept of revenue management and describe it as a mainstream business practice with a growing list of industry users, ranging from airlines, hotels, and resorts to car rental companies. "The economic impact of revenue management is significant, with increases in revenue of 5% or more reported in several industry applications of revenue management systems" (Talluri & Van Ryzin, 2005, p. 142). This work also provides a conceptual framework that explains why and how businesses manage revenues, given customer heterogeneity, demand variability, production inflexibility, data and information infrastructure, and management culture. Talluri and Van Ryzin (2005) also suggest that, historically, retailing, energy, airlines, and manufacturing are among the sectors in which revenue management is most necessary. They discuss how firms use IT systems such as point-of-sale, enterprise resource planning, supply chain management, and customer relationship management to facilitate revenue management. As discussed above, revenue management is essential to healthcare. Furthermore, given high levels of regulation in hospitals and limitations on how much revenue healthcare providers can generate, we would expect specialized health IT systems to facilitate hospital revenue management.

In this paper, we examine revenue management performance through two metrics: increase of net patient revenue and reduction of uncompensated care. We refer to these two measures in the following section in which we develop our hypotheses.

3 Hypotheses Development

3.1 IT and Net Patient Revenue

Following the previous literature, we first examine the effect of IT on net patient revenue (NPR) as the first dependent variable. NPR is simply the outcome measure of a hospital's revenue management performance. Devaraj and Kohli (2000, 2003) use NPR as a main dependent variable of hospital performance. Devaraj, Ow, and Kohli (2013) suggest that performance measures must consider hospital-wide criteria as opposed to unit-level functional criteria, which can result in suboptimization (Roth & van Dierdonck, 1995). Alternative measures such as cost and profitability, even though commonly used, are affected by the terms of contracts with insurance companies, while NPR is more meaningful for hospitals because it is a consistent measure of the extent of services a hospital provides and is unaffected by discounted reimbursement or by the local competitive environment. In their study, Devaraj, Ow, and Kohli (2013) examine the impact of IT investment on the swiftness and evenness of patient flow and subsequently on hospital performance (measured by NPR) and find positive relationships—namely, IT investment in hospitals can lead to improved performance from the two channels of effectiveness and efficiency. Effectiveness relates to doing things in a way that leads to expected or desired outcomes (Devaraj, Ow, & Kohli, 2013), and efficiency refers to the ability to produce higher output (i.e., see more patients) for a given set of inputs. We argue that clinical IT systems contribute meaningfully to the effectiveness part of performance because they can help medical providers improve diagnoses and treatment, whereas business IT systems focus more on the efficiency side of the business. Since this study is on revenue management, it will be helpful to first examine whether IT impacts the ultimate outcome of revenue at all before investigating the underlying mechanism. Overall, we argue that IT investment makes patient care more effective and efficient, thus helping to bring in more revenue. We first examine the short-term contemporaneous effect and argue that IT investment has instantaneous effects. Therefore, we hypothesize that:

H1a: Clinical IT (CIT) has positive short-term effects on net patient revenue.

H1b: Business IT (BIT) has positive short-term effects on net patient revenue.

Research has also noted that there are complementarities between IT and organizational processes (Barua & Mukhopadhyay, 2000; Pavlou & El Sawy, 2006). Brynjolfsson and Hitt (2003) discuss how important organizational transformation is for successful IT adoption. Kalakota and Robinson (2003) also suggest that complementarities facilitate the seamless integration of IT and business processes or "activity systems" such as customer relationships, operations, financial, and human resource management. Prior research on IT in a non-healthcare context suggests that organizations often require time to learn and adapt to IT systems and that organizations incur time lags before expected returns manifest (Brynjolfsson & Hitt, 2003; Curley & Pyburn, 1982). In the hospital setting, Devaraj and Kohli (2003) find that even though technology usage was positively and significantly associated with measures of hospital revenue and quality, this effect occurred only after time lags, suggesting that complementarities between IT adoption and organizational transformation or process redesign are vital to the success of technology adoption. Therefore, investments in IT might not pay off instantaneously because organizational process adaptation and organizational learning must first occur. Indeed, in its initial phases, IT adoption may appear to make the organization less efficient. Markus and Tanis (2000) map out the process of implementing enterprise IT systems and highlight the notion that things get worse before they get better. In the healthcare sector, Sidorov (2006) notes the high cost of adoption and cites evidence that EMR leads to greater health spending and reduced provider productivity (Dranove et al., 2014). Therefore, the question of how IT relates, if at all, to revenue management is not only one of effect, but is also likely a question of timing. As a result, this study will also address the following research question: *If IT does facilitate revenue management in hospitals, how long it will take it to manifest?*

Based on complementarity theory, we anticipate lagged effects of up to three years because IT systems are usually complex, and physicians other end users need time to learn and develop expertise (Dranove, 1988; Dranove et al., 2014). That is, IT adoption may not be able to provide value for the hospitals immediately following the adoption; rather, value begins to appear only after physicians, nurses, and administrators acquire sufficient familiarity and expertise in working with the system. Therefore, we hypothesize that:

H2a: CIT has positive long-term effects on net patient revenue.

H2b: BIT has positive long-term effects on net patient revenue.

3.2 IT and Uncompensated Care

Many of the characteristics described by Talluri and Van Ryzin (2005) are also present in the healthcare sector. Patients are heterogeneous in terms of conditions and willingness (ability) to pay. However, unlike other industries, where businesses can price discriminate and refuse to serve certain customers, how much a hospital can charge is usually subject to regulations and constrained by fee cap. Also, hospitals often cannot turn away patients because of their condition or ability to pay. Therefore, uncompensated care is a bane of hospitals. Uncompensated care typically refers to the sum of a hospital's unreimbursed care expenses incurred, for example, by the inability of patients to pay their bills, faulty insurance documents, obsolete patient information, or patients' unwillingness to pay for their care. Because hospitals cannot turn away patients that are critically ill, they are often reconciled to accepting that a proportion of expenses will not be reimbursed. Uncompensated care costs are nontrivial for most hospitals. In 2013, US hospitals claimed $46.4 billion in uncompensated care, representing 5.9% of their total costs (AHA, 2015). Hospitals often lump charity care and uncompensated care expenses together into one category. To the extent that a hospital can distinguish between charity care and bad debts, it can identify mechanisms to reduce the bad-debt portion of uncompensated care by improving collection techniques or decreasing care costs. We argue that IT systems can offer hospitals the capability to lower uncompensated care expenses through mechanisms such as improved patient information, more accurate insurance verification and record keeping, outsourcing receivables management, and designing better payment mechanisms. IT can lower the cost of the bad-debt portion of uncompensated care and help hospitals locate additional mechanisms for covering uncompensated care. Also, if a hospital adopts advanced clinical IT systems, it could increase efficiency in care delivery by preventing unnecessary or repetitive diagnoses, checks, and medications. Moreover, even when bad debt occurs, having the right business IT systems in place could help hospitals collect unpaid amounts from patients or locate third-party resources or subsidies to help cover such costs. As mentioned above, we first explore the contemporaneous effect of IT on the uncompensated care ratio. Therefore, we hypothesize that:

H3a: CIT has negative short-term effects on the uncompensated care ratio.

H3b: BIT has negative short-term effects on the uncompensated care ratio.

Using the same rationale, since it takes a long time for stakeholders to learn and hospitals to adapt to technological adoption with business process reengineering, we speculate that investment in IT might take years to be effective. Therefore, we hypothesize that:

H4a: CIT has negative long-term effects on the uncompensated care ratio.

H4b: BIT has negative long-term effects on the uncompensated care ratio.

3.3 Moderating Effects of Hospital Size and Type

We are also interested in exploring the heterogeneous effects of IT on revenue management across hospital characteristics as IT may not be equally helpful and valuable for all hospitals. Hospital size is one factor that might moderate hypothesized relationships between IT and revenue management performance. The same IT system might not be as useful and helpful for revenue management for small hospitals as it is for larger ones. For larger hospitals, because of their resources, once on track, they might outperform their small counterparts, as many of those IT systems are specifically designed for and thus more valuable to large organizations. Therefore, we hypothesize that:

H5a: Hospital size interacts with CIT to predict long-term revenue management performance such that the positive long-term effects of CIT on net patient revenue and the negative long-term effects of CIT on the uncompensated care ratio are stronger for larger hospitals.

H5b: Hospital size interacts with BIT to predict long-term revenue management performance such that the positive long-term effects of BIT on net patient revenue and the negative long-term effects of BIT on the uncompensated care ratio are stronger for larger hospitals.

Another important hospital characteristic is its institutional background or mission. US hospitals can be broadly classified as nonprofit and for-profit hospitals, with different missions, respectively. Prior literature suggests that the objective functions of nonprofit hospitals are not merely focused on profit maximization but rather include provisions for appropriate levels of quality, quantity, and access to a range of services (Dranove, 1988; Eldenburg et al., 2011; Hoerger, 1991; Krishnan, Joshi, & Krishnan, 2004; Leone & Van Horn, 2005; Newhouse, 1970; Pauly & Redisch, 1973). The revenue management model of nonprofit hospitals thus differs accordingly. The IRS allows tax exemptions for nonprofit hospitals that provide so-called "community benefits" including charity care (uncompensated), medical education, subsidized health services, community health improvement activities, etc.[2] Therefore, nonprofit hospitals must also focus on ensuring nonfinancial outcomes, such as provision of care for indigent patients, medical education, and provision of services for the community (Frank & Salkever, 1994), and seek to provide such services even if they are unprofitable. Economists have studied the systematic difference in behavior regarding loss between nonprofit and for-profit hospitals. Dranove, Garthwaite, & Ody (2017) have examined how nonprofit hospitals responded to the sharp reductions in their assets caused by the 2008 stock market collapse and found that the average hospital neither raised prices nor reduced treatment costs. Part of the reason for this could be related to their nonprofit status and associated revenue model, i.e., they might be entitled to more charity donations or subsidies from government agencies or other social groups or tax benefits if they experience financial hardship and provide high levels of uncompensated care. Therefore, nonprofit hospitals may be less motivated than their for-profit counterparts to use IT to minimize the amount of uncompensated care provided. Therefore, we hypothesize that:

H6a: Hospital type (nonprofit vs. for-profit) interacts with CIT to predict revenue management performance such that the positive long-term effects of CIT on net patient revenue and the negative long-term effects of CIT on the uncompensated care ratio are weaker for nonprofit hospitals.

H6b: Hospital type (nonprofit vs. for-profit) interacts with BIT to predict revenue management performance such that the positive long-term effects of BIT on net patient revenue and the negative long-term effects of BIT on the uncompensated care ratio are weaker for nonprofit hospitals.

4 Methodology

4.1 Overview

Our empirical analyses use data from two sources: the Healthcare Information and Management Systems Society (HIMSS) Analytics database and hospital-level data from the Office of Statewide Health Planning and Development (OSHPD) of California. Because of data availability limitations, we restrict our analyses to hospitals located in the state of California. Being in the same state also controls for variations in the regulatory environment of the state in which the hospital is located. The HIMSS dataset reports the status and implementation history of health IT for more than 5,300 healthcare providers nationwide (Li, 2014). HIMSS classifies IT applications into several categories. We label these applications as either clinical or business IT based on their purpose or use. Hospital and patient-level financial and nonfinancial data are reported by the OSHPD annually. We exclude specialty hospitals since these hospitals operate substantially differently and are not subject to the same regulations (Eldenburg et al., 2011).

[2] "How Much Charity Care Do Not-For-Profit Hospitals Provide?" (http://www.modernhealthcare.com/article/20170424/blog/170429935)

4.2 Variable Definitions

4.2.1 Independent Variables

IT measures are from the HIMSS database between 2002 and 2012. We examined the depth of both clinical and business IT applications. Depth refers to the count of live and operational clinical IT applications in a hospital in a given year. There are subcategories of IT systems for both clinical and business categories. After obtaining the summary statistics on the number of IT applications adopted in each subcategory, we derived a more relevant set of subcategories, presented in Table 1, that we used to calculate clinical and business IT depth, respectively—since some subcategories are rarely adopted, their inclusion in the calculation of overall IT depth can thus lead to estimation biases. Finally, we calculated the normalized clinical and business IT depth by dividing the raw number of IT systems adopted in a respective category in a given year by the maximum number of IT systems adopted by a hospital in a given year. Since the maximum number of clinical IT systems adopted by a hospital in a single year is 51, that hospital's normalized clinical IT depth is 1 and all other hospitals are given a normalized clinical IT depth score that is calculated by dividing the hospital's raw value by this max value, yielding results ranging from 0 to 1. Normalized business-IT depth measured is similarly constructed. This transformation gives us the ability to show the impact of IT investment relative to competitors and increases the magnitude of the estimation coefficients in the regressions, which makes the results more interpretable.

Table 1. List of Clinical and Business IT Categories

Clinical IT category	Business IT category
Cardiology & PACS	Financial decision support
ED or respiratory	General financials
Electronic medical record	Human resources
Health information management (HIM)	Revenue cycle management
Laboratory	Supply chain management
Nursing	Utilization review/risk management
Pharmacy	
Radiology & PACS	

Table 2. Variable Definitions

Variable	Operationalization
Dependent variables	
Net patient revenue	Total patient revenue
Uncompensated care ratio	Total uncompensated revenue divided by total patient revenue
Independent variables	
Clinical IT depth (CIT)	Number of live and operational clinical IT applications implemented by the hospital
Business IT depth (BIT)	Number of live and operational business IT applications implemented by the hospital
Control variables	
Church hospital	Dummy variable of 1 if the hospital is church owned, 0 otherwise
Nonprofit hospital	Dummy variable of 1 if the hospital is nonprofit, 0 otherwise
Teaching hospital	Dummy variable of 1 if the hospital has medical residents, 0 otherwise
Hospital size	Logarithm of total number of discharges
% of Medicare patient days	Number of Medicare patient days divided by total number of patient days
% of indigent patient days	Number of indigent patient days divided by total number of patient days
Cost as % of revenue	Total cost divided by total patient revenues
ROA t-1	Return on asset of the previous year
Industry concentration	Herfindahl-Hirschman index: sum of squared market shares per local market
Case mix index (CMI)	Case mix index of the hospital

Table 3. Descriptive Statistics

Variable	Obs.	Mean	*SD*	Min	25% Pctl.	Median	75% Pctl.	Max
Dependent variables								
Net patient revenue ($10 million)	2,747	52.6916	57.988	0.2929	13.823	34.9495	72.2898	526.0504
Uncompensated care ratio	3,155	0.023	0.0169	0.0007	0.0107	0.0191	0.0306	0.1002
Independent variables								
CIT (Normalized)	2,968	0.3193	0.1473	0	0.2	0.3	0.4375	1
BIT (Normalized)	2,968	0.4024	0.0917	0	0.3556	0.4	0.4444	1
Control variables								
Church hospital	3,459	0.1159	0.3202	0	0	0	0	1
Nonprofit hospital	3,459	0.4435	0.4969	0	0	0	1	1
Teaching hospital	3,459	0.2449	0.43	0	0	0	0	1
Hospital size	3,390	8.6198	1.2115	4.2485	8.0124	8.8623	9.5535	10.395
% of Medicare patient days	3,309	0.7535	0.1272	0.3258	0.68	0.7659	0.8438	0.99
% of indigent patient days	2,726	0.0299	0.0319	0.0003	0.0075	0.0196	0.0429	0.2032
Cost as % of revenue	3,219	0.3092	0.1295	0.1107	0.2258	0.2726	0.3562	0.8811
ROA t-1	2,883	0.04	0.1265	-0.4686	-0.0122	0.0408	0.1	0.4859
Industry concentration	3,432	834.0283	446.554	219.273	534.125	802.898	1165.53	1866.91
Case mix index (CMI)	3,388	1.1444	0.2726	0.67	0.96	1.1	1.2675	2.65

Table 4. Correlation Matrix

	NPR	UCR	CIT t	CIT t-1	CIT t-2	CIT t-3	BIT t	BIT t-1	BIT t-2
Net patient revenue ($10 million)	1								
Uncompensated care ratio	-0.3595	1							
CIT t	0.4976	-0.1939	1						
CIT t-1	0.4817	-0.1756	0.8574	1					
CIT t-2	0.4616	-0.1427	0.7521	0.8937	1				
CIT t-3	0.4397	-0.13	0.6641	0.7939	0.8881	1			
BIT t	0.3785	-0.1652	0.6292	0.6114	0.5798	0.5239	1		
BIT t-1	0.3605	-0.1724	0.5752	0.6116	0.5805	0.5518	0.8349	1	
BIT t-2	0.3515	-0.1607	0.542	0.5721	0.5946	0.57	0.7074	0.8334	1
BIT t-3	0.338	-0.1551	0.5227	0.5274	0.5347	0.5722	0.6144	0.6988	0.8142
Church hospital	0.0364	-0.1318	-0.0221	-0.0265	-0.0185	-0.0188	0.0056	0.0032	-0.0148
Nonprofit hospital	0.1659	-0.22	0.168	0.1472	0.1315	0.1273	0.0209	0.0281	0.0476
Teaching hospital	0.3631	-0.1043	0.1633	0.1369	0.1053	0.0804	0.1491	0.1583	0.1385
Hospital size	0.6828	-0.3085	0.4787	0.4142	0.3675	0.3423	0.3181	0.319	0.3062
% of Medicare patient days	-0.1455	0.1642	-0.2102	-0.1576	-0.1247	-0.1024	-0.0869	-0.0887	-0.0984
% of indigent patient days	0.0904	-0.0224	0.0779	0.0798	0.0582	0.041	0.0437	0.0455	0.0286
Cost as % of revenue	-0.3254	0.2247	-0.0911	-0.1079	-0.1155	-0.1202	-0.1303	-0.1302	-0.1367
Return on asset (ROA) t-1	0.1161	-0.0508	0.1769	0.1674	0.1418	0.1236	0.1512	0.1668	0.168
Herfindahl-Hirschman index (HHI)	0.0364	0.0126	0.0099	0.0098	0.0084	0.0019	0.0198	0.0188	0.0224
Case mix index (CMI)	0.5366	-0.3441	0.3583	0.3685	0.3689	0.368	0.2381	0.2263	0.214

4.2.2 Dependent Variables

Net patient revenue is measured as total patient revenue reported in the OSHPD database. The uncompensated care ratio is defined as the percentage of uncompensated care compared to total patient revenue.

4.2.3 Control Variables

We also include a set of hospital and market characteristics as control variables for revenue management performance. Controls include dummy variables that indicate whether a hospital is church-owned, a teaching hospital, or a nonprofit (vs. for-profit) hospital. Other hospital-level controls include the percentage of Medicare patient days and the percentage of indigent patient days. As described in Li (2014), in addition to diagnostic-related grouping (DRG) weights, the reimbursement amount a hospital can receive for a DRG depends on other factors such as teaching hospital status and the share of indigent patients treated. Church-owned hospitals may be able to access additional sources of reimbursement and may thus have fewer incentives to implement revenue enhancement practices. We control for hospital size by including the natural logarithm of the number of discharges, as larger hospitals might have greater regulatory clout (Carpenter, 2004; Heese, Krishnan, & Moers, 2016), and also control for the hospital's cost as a percentage of revenue and return on assets in the previous year. We use the Herfindahl-Hirschman index (HHI) to control for the influence of competition, calculating HHI according to the market shares of each hospital in the local market (i.e., health service area). Finally, we control for the hospital's case mix index (CMI), which captures the average severity of illness of patients and controls, to evaluate whether a hospital admits more severely ill patients. Table 2 summarizes all the variables used in this study, which were winsorized at the 1% and 99% level. Descriptive statistics of all variables are reported in Table 3, and Table 4 presents the correlations between all variables.

4.2.4 Model Estimation

To test the first four hypotheses, we defined the "short-term" and "long-term" effects of clinical IT (CIT) and business IT (BIT) based on the recommended approach (Seetharaman, 2004; Wooldridge, 2015). More specifically, as shown in Equation (1), the short-term effect can be estimated from the coefficients β_1 and β_2, which are measures of the contemporaneous relationship between revenue management and CIT and BIT, respectively. In order to test H1 and H3, we regressed revenue management performance (i.e., $\text{revenue}_{i,t} = \{\log(NPR_{i,t}), \log(\text{UCR}_{i,t})\}$)[3] at time t based on the contemporaneous effect of CIT and BIT, as indicated in the model:

$$\text{revenue}_{i,t} = \alpha_1 \text{revenue}_{i,t-1} + \beta_1 \text{CIT}_{i,t} + \beta_2 \text{BIT}_{i,t} + X_{i,t}\gamma + u_i + \lambda_t + v_{i,t} \;, \tag{1}$$

where subscript i refers to hospital, t represents the year, CIT_t indicates the clinical IT depth at year t, BIT_t indicates the business IT depth at year t, $X_{i,t}$ are control variables for hospital characteristics, and $v_{i,t}$ is the error term. The fixed effect u_i measures any time-invariant heterogeneity at the hospital level and λ_t is the year dummies. Then, to test H2 and H4, the long-term effects can be estimated from the sum of the coefficients on the current and lagged CIT, $\beta_1 + \beta_2 + \beta_3 + \beta_4$, (lagged BIT, $\beta_5 + \beta_6 + \beta_7 + \beta_8$),[4] which is the long-run change in revenue management given a permanent increase in CIT (and BIT) and is called the *long-run propensity* (Seetharaman, 2004; Wooldridge, 2015), in Equation (2).

$$\begin{aligned} \text{revenue}_{i,t} = {} & \alpha_1 \text{revenue}_{i,t-1} + \beta_1 \text{CIT}_{i,t} + \beta_2 \text{CIT}_{i,t-1} + \beta_3 \text{CIT}_{i,t-2} + \beta_4 \text{CIT}_{i,t-3} + \beta_5 \text{BIT}_{i,t} + \beta_6 \text{BIT}_{i,t-1} \\ & + \beta_7 \text{BIT}_{i,t-2} + \beta_8 \text{BIT}_{i,t-3} + X_{i,t}\gamma + u_i + \lambda_t + v_{i,t} \end{aligned} \tag{2}$$

It is important to note that to test the short-term and long-term effects, we conducted the "t-test" and "F-test," respectively. The model represented by Equation (3) is used next to estimate the moderating effect of hospital size and type on the long-term relationship between CIT (and BIT) and revenue management. More specifically, the coefficients ($\sum_{s=0} \delta_{s+1}$ and $\sum_{s=0} \delta_{s+5}$) of the interaction variables capture the moderating effect of hospital size on revenue management in Equation (3). Similarly, the coefficients ($\sum_{s=0} \delta_{s+1}$ and $\sum_{s=0} \delta_{s+5}$) of interaction variables capture the moderating effect of hospital type (for-profit vs. nonprofit) on revenue management in Equation (4).

[3] NPR = Net Patient Revenue and UCR = Uncompensated Care Ratio.

[4] We chose the lag length using data-dependent methods, such as AIC and BIC, rather than arbitrarily selecting the number of lags, and the optimal lag order using AIC and BIC consistently appears to be 3 in our GMM approach.

$$\text{revenue}_{i,t} = \alpha_1 \text{revenue}_{i,t-1} + \sum_{s=0} \beta_{s+1} \text{CIT}_{i,t-s} + \sum_{s=0} \beta_{s+5} \text{BIT}_{i,t-s} + \beta_9 \text{size}_{i,t} + \sum_{s=0} \delta_{s+1} \text{size}_{i,t} \times \text{CIT}_{i,t-s} + \sum_{s=0} \delta_{s+5} \text{size}_{i,t} \times \text{BIT}_{i,t-s} + X_{i,t}\gamma + u_i + \lambda_t + \upsilon_{i,t} \tag{3}$$

$$\text{revenue}_{i,t} = \alpha_1 \text{revenue}_{i,t-1} + \sum_{s=0} \beta_{s+1} \text{CIT}_{i,t-s} + \sum_{s=0} \beta_{s+5} \text{BIT}_{i,t-s} + \beta_9 \text{nonprofit}_{i,t} + \sum_{s=0} \delta_{s+1} \text{nonprofit}_{i,t} \times \text{CIT}_{i,t-s} + \sum_{s=0} \delta_{s+5} \text{nonprofit}_{i,t} \times \text{BIT}_{i,t-s} + X_{i,t}\gamma + u_i + \lambda_t + \upsilon_{i,t} \tag{4}$$

In order to test the moderating effects of hospital size and type, we conducted the *F*-test. Measuring the effect of CIT and BIT on hospital-level revenue management is likely to be subject to identification issues and endogeneity, as is typically the case with observational studies (Guide Jr. & Ketokivi, 2015; Roberts & Whited, 2012). Unlike in an experimental setting where the researcher is able to manipulate the treatment conditions, in observational research the researcher is merely able to *observe* the treatment conditions (Ketokivi & McIntosh, 2015). Therefore, ordinarily, the researcher may not always be able to know the exact origins of the variances. A sample of a hospital's increased CIT and BIT is nonrandom, since hospitals will only increase IT investment if they satisfy specific criteria, and even then, they may decide to maintain the status quo. This may lead to an omitted variable bias wherein the unobserved, yet satisfied, criteria are not being measured and are therefore uncontrolled for in the model. Thus, to control for endogeneity in this study, we took several specific steps.

First, to account for endogeneity stemming from the omitted variable bias, the lagged dependent variable was also included as shown in the above equations. This approach controls for unobservable omitted variables (Dess et al., 1995; Godfrey & Hill, 1995) and reflects the possibility that changes in the covariates affect the dependent variable over multiple periods (Fomby, Hill, & Johnson, 2012; Hitt, Gimeno, & Hoskisson, 1998). Furthermore, the inclusion of the lagged dependent variable enhances the causal inferences that can be drawn (Hitt et al., 1998). Second, we use dynamic panel data models and rely on the generalized method of moments (GMM) to estimate the lagged dependent models (Hansen, 1982). Introducing a lagged dependent variable in Equations 1-4 would ordinarily be biased and inconsistent because it would be correlated with the incorrect term. Therefore, conventional OLS estimation of the above dynamic model would produce biased results. To mitigate this problem, we used lags of the explanatory variables as instruments to achieve consistent estimators (Anderson & Hsiao 1981; Anderson & Hsiao, 1982).

GMM estimators for panel data[5] have become very popular and have attained a leading role among dynamic panel data estimators because they produce consistent estimates in a dynamic regression model with both endogenous explanatory variables and the presence of measurement error (Di Liberto, Pigliaru, & Mura, 2008). The GMM panel estimator directly controls for the potential bias induced by the omission of hospital-specific effects and endogeneity. GMM also has the advantage of minimizing the loss of degrees of freedom when the number of instruments is large, relative to the number of observations, which is an important feature in the context of this study, given that the number of time periods in our dataset is small, relative to the number of hospitals.

However, GMM estimators may suffer from instrument proliferation when the number of moments[6] conditions increases because of the dimension of the vector of explanatory variables. To resolve this issue, we use Roodman's (2009) recommended approach and limit the lag length to adjacent lags (e.g., t-3 and t-4) in order to reduce the number of counts. To test the hypotheses, we do not use all available moment conditions because adjacent lags contain more informative instruments than very remote lags. In order to check the model specification, we conducted a second-order autocorrelation test AR(2) and Sargan's overdispersion test. We relied on the Sargan test instead of the Hansen test because, while the Sargan test is not weakened by the presence of numerous instruments, the Hansen test is. The standard diagnostic statistics attest to the validity of the instrumentation at a 5% significance level (Model 1 in Table 5, p-value = 0.11; Model 2 in Table 5, p-value =

[5] Especially in the formulations of Arellano and Bond (1991) and Arellano and Bond (1995) /Blundell and Bond (1998). Both are general estimators designed for situations that have few time periods and many individuals.

[6] GMM estimation strategy uses the moment conditions $E(y_{i,t-s}\Delta\upsilon_{i,t}) = 0$, where $y_{i,t-s}$ indicates outcome variable for $t = 4, \ldots, T$ and $s \geq 2$. This is why this strategy is called the generalized method of moments (GMM).

0.55; Model 3 in Table 5, p-value = 0.63; Model 4 in Table 5, p-value = 0.31; Model 1 in Table 7, p-value = 0.85; Model 2 in Table 7, p-value = 0.54; Model 1 in Table 9, p-value = 0.58; Model 2 in Table 9, p-value = 0.51).

The Sargan statistic implies that the test of overidentifying restrictions cannot reject its null hypothesis; the test therefore led us to retain the validity of the instruments. As expected, the first order is significant based on the Arellano-Bond test for AR(1) because of the lagged dependent variable (Arellano & Bond, 1991), thereby rejecting the null hypothesis that there is no first-order serial correlation. However, in this study, we were unable to reject the test for second-order serial correlations of AR(2), which thus supports the validity of using lags of 2 and longer as GMM instruments (Arellano & Bond, 1991). Therefore, these results offer further support for our model specification.

5 Empirical Results

5.1 Short- and Long-Term Effects of CIT and BIT on Net Patient Revenue

In H1a and H1b, we posit that the short-term effects of CIT and BIT are associated with higher net patient revenue for the hospital. As shown in Model 1 in Table 5, the results indicate that CIT and BIT have a positive and statistically significant association with net patient revenue ($\beta = 0.093$, p-value < 0.01; $\beta = 0.080$, p-value < 0.05, respectively). In H2a and H2b, we posit that the long-term effects of CIT and BIT are associated with higher hospital patient revenue. As shown in Equations (1) and (2) in Table 6, the results indicate that CIT and BIT have a positive and statistically significant joint effect with net patient revenue ($\sum_{s=0}^{3} \beta_{s+1}^{2} = 0.166$, p-value $= 0.002$; $\sum_{s=0}^{3} \beta_{s+5}^{2} = 0.163$, p-value $= 0.027$, respectively). These results suggest CIT and BIT have positive and statistically significant short- and long-term effects on net patient revenue. Thus, we found support for H1a, H1b, H2a, and H2b.

5.2 Short- and Long-Term Effects of CIT and BIT on the Uncompensated Care Ratio

In H3a and H3b, we posit that the short-term effects of CIT and BIT are associated with a lower uncompensated care ratio. As shown in Model 3 in Table 5, the results indicate that CIT has a negative and statistically significant association with the uncompensated care ratio ($\beta = -0.279$, p -value < 0.05). However, there is no statistically significant association between BIT and the uncompensated care ratio in hospitals ($\beta = -0.191$, p-value $= 0.358$). Furthermore, as shown in Equations (3) and (4) in Table 6, the results indicate that CIT and BIT have a statistically insignificant joint effect on the uncompensated care ratio ($\sum_{s=0}^{3} \beta_{s+1}^{2} = -0.141$, p-value $= 0.236$; $\sum_{s=0}^{3} \beta_{s+5}^{2} = -0.100$, p-value $= 0.332$, respectively). Thus, we found only a short-term effect of CIT on the uncompensated care ratio; H3a is supported, but H3b, H4a, and H4b are not supported.

5.3 Interaction Effect of Hospital Size with CIT and BIT on Long-Term Revenue Management

In H5a, we posit that the hospital size moderates the relationship between the long-term effects of CIT and revenue management (net patient revenue and the uncompensated care ratio). As shown in Equations (1) and (2) in Table 8, there is no statistically significant moderating effect of hospital size on the relationship between the long-term effects of CIT and net patient revenue ($\sum_{s=0}^{3} \delta_{s+1}^{3} = -0.313$, p-value$= 0.896$) as well as the uncompensated care ratio ($\sum_{s=0}^{3} \delta_{s+1}^{3} = -0.013$, p-value$= 0.480$). However, as shown in Equations (3) and (4) in Table 8, we found that hospital size does moderate the relationship between the long-term effects of BIT and net patient revenue ($\sum_{s=0}^{3} \delta_{s+5}^{3} = 0.793$, p-value$= 0.026$) as well as the uncompensated care ratio ($\sum_{s=0}^{3} \delta_{s+5}^{3} = -1.613$, p-value< 0.01). These results suggest that both the positive long-term effects of BIT on net patient revenue and the negative long-term effects of BIT on the uncompensated care ratio are stronger for larger hospitals: i.e., H5a is not supported but H5b is supported.

5.4 Interaction Effect of Hospital Type with CIT and BIT on Long-Term Revenue Management

In H6a, we posit that the hospital type moderates the relationship between the long-term effects of CIT and revenue management (net patient revenue and the uncompensated care ratio). As shown in Equations (1) and (2) in Table 10, there is a statistically significant moderating effect of hospital type on the relationship between the long-term effects of CIT and net patient revenue ($\sum_{s=0}^{3} \delta_{s+1}^{4} = -0.477$, p-value$= 0.043$) as well as the uncompensated care ratio ($\sum_{s=0}^{3} \delta_{s+1}^{4} = 2.023$, p-value $= 0.027$). However, as shown in Equations (3) and (4) in Table 10, we found that there is no moderating effect of hospital type on the relationship between the long-term effects of BIT and net patient revenue ($\sum_{s=0}^{3} \delta_{s+5}^{4} = 0.567$, p-value$= 0.920$) as well as the uncompensated care ratio ($\sum_{s=0}^{3} \delta_{s+5}^{4} = 2.759$, p-value $= 0.101$). These results suggest that the positive long-term effects of CIT on net patient revenue as well as the negative long-term effects of CIT on the uncompensated care ratio are weaker for nonprofit hospitals: i.e., H5a is supported but H5b is not supported.

Table 5. Contemporaneous and Lagging Effects of CIT and BIT on Revenue Management Performance

	DV = $\log(\mathrm{NPR}_t)$		DV = $\log(\mathrm{UCR}_t)$	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Lagged DV	0.620*** (0.015)	0.495*** (0.034)	0.578*** (0.041)	0.644*** (0.053)
$\mathbf{CIT}_t$	0.093*** (0.024)	0.113** (0.058)	-0.279** (0.139)	0.488 (0.323)
$\mathbf{CIT}_{t-1}$	-	-0.033 (0.051)	-	-0.892*** (0.292)
$\mathbf{CIT}_{t-2}$	-	0.024 (0.026)	-	0.588*** (0.165)
$\mathbf{CIT}_{t-3}$	-	0.061** (0.025)	-	-0.325*** (0.123)
$\mathbf{BIT}_t$	0.080** (0.032)	0.209*** (0.067)	-0.191 (0.208)	-1.244*** (0.337)
$\mathbf{BIT}_{t-1}$	-	-0.159*** (0.056)	-	1.055*** (0.276)
$\mathbf{BIT}_{t-2}$	-	0.031 (0.027)	-	-0.169 (0.161)
$\mathbf{BIT}_{t-3}$	-	0.083** (0.035)	-	0.259 (0.182)
Controls	Included	Included	Included	Included
Year dummy	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
N	265	267	263	254
N×T	1,874	1,750	1,880	1,762
Sargan test p-value	0.11	0.55	0.63	0.31
# of instruments	163	107	117	107
$\boldsymbol{m1}$	-3.98***	-4.30***	-6.39***	-6.84***
$\boldsymbol{m2}$	-0.10	-0.83	1.81*	1.41
Wald test	$\chi^2(24) =$ 160,300.87***	$\chi^2(30) =$ 613,761.35***	$\chi^2(24) =$ 1,902.87***	$\chi^2(24) =$ 251,965.69***

Note: *, **, *** indicates significance level of 10%, 5%, and 1%, respectively; NPR = net patient revenue; UCR = uncompensated care ratio; CIT = clinical IT; BIT = business IT.

Table 6. Testing H2 and H4: Combined Lagging Effects of CIT and BIT on Revenue Management Performance

Equation	**Estimation model in Table 5**	**Independent variable**	$\mathbf{H_0}$	$\mathbf{H_A}$	**Dependent variable**	**Test statistic** (z)	$\boldsymbol{p}$**-value (one-sided)**
(1)	Model 2	$\sum_{s=0} \mathrm{CIT}_{t-s}$	$\sum_{s=0} \beta_{s+1} = 0$	$\sum_{s=0} \beta_{s+1} > 0$	$\log(\mathrm{NPR_t})$	2.82	0.002
(2)	Model 2	$\sum_{s=0} \mathrm{BIT}_{t-s}$	$\sum_{s=0} \beta_{s+5} = 0$	$\sum_{s=0} \beta_{s+5} > 0$	$\log(\mathrm{NPR_t})$	1.92	0.027
(3)	Model 4	$\sum_{s=0} \mathrm{CIT}_{t-s}$	$\sum_{s=0} \beta_{s+1} = 0$	$\sum_{s=0} \beta_{s+1} < 0$	$\log(\mathrm{UCR_t})$	-0.72	0.236
(4)	Model 4	$\sum_{s=0} \mathrm{BIT}_{t-s}$	$\sum_{s=0} \beta_{s+5} = 0$	$\sum_{s=0} \beta_{s+5} < 0$	$\log(\mathrm{UCR_t})$	-0.44	0.332

Table 7. Moderating Effects of Hospital Size on the Relationships between CIT / BIT and Revenue Management Performance

	DV = $\log(\text{NPR}_t)$ Model 1	DV = $\log(\text{UCR}_t)$ Model 2
Lagged DV	0.704*** (0.064)	0.623*** (0.029)
CIT_t	1.024** (0.464)	3.231*** (0.715)
CIT_{t-1}	-0.859 (0.607)	-2.654*** (0.827)
CIT_{t-2}	1.095* (0.582)	-2.061*** (0.587)
CIT_{t-3}	0.0005 (0.371)	1.242*** (0.475)
BIT_t	-1.727** (0.742)	-0.125 (1.073)
BIT_{t-1}	-0.292 (0.724)	2.576*** (0.841)
BIT_{t-2}	-1.588** (0.673)	1.369** (0.659)
BIT_{t-3}	0.867* (0.471)	-0.260 (0.541)
size	0.042 (0.162)	0.682*** (0.162)
size $\times$ CIT_t	-0.216 (0.167)	-0.847*** (0.282)
size $\times$ CIT_{t-1}	0.247 (0.219)	0.369 (0.333)
size $\times$ CIT_{t-2}	-0.278 (0.231)	1.153*** (0.237)
size $\times$ CIT_{t-3}	-0.065 (0.149)	-0.688*** (0.191)
size $\times$ BIT_t	0.567** (0.261)	-0.391 (0.402)
size $\times$ BIT_{t-1}	-0.061 (0.280)	-0.647** (0.208)
size $\times$ BIT_{t-2}	0.613** (0.286)	-0.711*** (0.268)
size $\times$ BIT_{t-3}	-0.326* (0.191)	0.135 (0.207)
Controls	Included	Included
Year dummy	Yes	Yes
Hospital FE	Yes	Yes
N	256	255
N×T	1,750	1,723
Sargan test p-value	0.85	0.54
# of instruments	84	163
$m1$	-3.45***	-7.41***
$m2$	1.30	1.35
Wald test	$\chi^2(38)$ = 8,521.55***	$\chi^2(38)$ = 398,086.16***

Table 8. Testing H5: Moderating Effects of Hospital Size on the Relationships between CIT / BIT and Revenue Management Performance

Equation	Estimation model in Table 7	Independent variable	H_0	H_A	Dependent variable	Test statistic (z)	p-value (one-sided)
(1)	Model 1	$\sum_{i=0} \text{size} \times \text{CIT}_{t-s}$	$\sum_{S=0} \delta_{s+1} = 0$	$\sum_{S=0} \delta_{s+1} > 0$	$\log(\text{NPR}_t)$	-1.25	0.896
(2)	Model 2	$\sum_{i=0} \text{size} \times \text{CIT}_{t-s}$	$\sum_{S=0} \delta_{s+1} = 0$	$\sum_{S=0} \delta_{s+1} < 0$	$\log(\text{UCR}_t)$	-0.05	0.480
(3)	Model 1	$\sum_{i=0} \text{size} \times \text{BIT}_{t-s}$	$\sum_{S=0} \delta_{s+5} = 0$	$\sum_{S=0} \delta_{s+5} > 0$	$\log(\text{NPR}_t)$	1.95	0.026
(4)	Model 2	$\sum_{i=0} \text{size} \times \text{BIT}_{t-s}$	$\sum_{S=0} \delta_{s+5} = 0$	$\sum_{S=0} \delta_{s+5} < 0$	$\log(\text{UCR}_t)$	-3.37	< 0.001

Table 9. Moderating Effects of Hospital Type (Nonprofit vs. For-profit) on the Relationships between CIT / BIT and Revenue Management Performance

	DV = $\log(\mathrm{NPR}_t)$ Model 1	DV = $\log(\mathrm{UCR}_t)$ Model 2
Lagged DV	0.562*** (0.061)	0.691*** (0.096)
$\mathbf{CIT}_t$	0.570*** (0.208)	1.779 (1.114)
$\mathbf{CIT}_{t-1}$	-0.201 (0.223)	-3.431** (1.374)
$\mathbf{CIT}_{t-2}$	-0.120 (0.195)	1.051 (1.271)
$\mathbf{CIT}_{t-3}$	0.133 (0.193)	-1.259 (0.964)
$\mathbf{BIT}_t$	-0.530 (0.329)	-4.307** (1.996)
$\mathbf{BIT}_{t-1}$	-0.192 (0.186)	2.460** (1.185)
$\mathbf{BIT}_{t-2}$	-0.088 (0.208)	-0.027 (1.681)
$\mathbf{BIT}_{t-3}$	0.231 (0.185)	0.693 (1.467)
nonprofit	-0.050 (0.131)	-1.849** (0.742)
nonprofit $\times \mathbf{CIT}_t$	-0.632*** (0.251)	-1.244 (1.213)
nonprofit $\times \mathbf{CIT}_{t-1}$	0.103 (0.251)	2.717* (1.535)
nonprofit $\times \mathbf{CIT}_{t-2}$	0.214 (0.238)	0.294 (1.431)
nonprofit $\times \mathbf{CIT}_{t-3}$	-0.162 (0.234)	0.256 (1.126)
nonprofit $\times \mathbf{BIT}_t$	0.686** (0.341)	4.227** (1.700)
nonprofit $\times \mathbf{BIT}_{t-1}$	-0.195 (0.282)	-0.848 (1.628)
nonprofit $\times \mathbf{BIT}_{t-2}$	0.154 (0.295)	1.459 (1.804)
nonprofit $\times \mathbf{BIT}_{t-3}$	-0.077 (0.242)	-2.079 (1.389)
Controls	Included	Included
Year dummy	Yes	Yes
Hospital FE	Yes	Yes
N	256	255
N×T	1,750	1,723
Sargan test p-value	0.85	0.54
# of instruments	79	79
$\boldsymbol{m1}$	-3.09***	-3.51***
$\boldsymbol{m2}$	-0.77	0.73
Wald test	$\chi^2(38)$ = 29,524.96***	$\chi^2(38)$ = 745.92***

Table 10. Testing H6: Moderating Effects of Hospital Type (Nonprofit vs. For-profit) on the Relationships between CIT / BIT and Revenue Management Performance

Equation	**Estimation model in Table 9**	**Independent variable**	$\mathbf{H_0}$	$\mathbf{H_A}$	**Dependent variable**	**Test statistic (z)**	$\boldsymbol{p}$**-value (one-sided)**
(1)	Model 1	$\sum_{i=0}$ nonprofit × CIT_{t-s}	$\sum_{S=0} \delta_{s+1} = 0$	$\sum_{S=0} \delta_{s+1} < 0$	$\log(\mathrm{NPR_t})$	-1.71	0.043
(2)	Model 2	$\sum_{i=0}$ nonprofit × CIT_{t-s}	$\sum_{S=0} \delta_{s+1} = 0$	$\sum_{S=0} \delta_{s+1} > 0$	$\log(\mathrm{UCR_t})$	1.92	0.027
(3)	Model 1	$\sum_{i=0}$ nonprofit × BIT_{t-s}	$\sum_{S=0} \delta_{s+5} = 0$	$\sum_{S=0} \delta_{s+5} < 0$	$\log(\mathrm{NPR_t})$	1.40	0.920
(4)	Model 2	$\sum_{i=0}$ nonprofit × BIT_{t-s}	$\sum_{S=0} \delta_{s+5} = 0$	$\sum_{S=0} \delta_{s+5} > 0$	$\log(\mathrm{UCR_t})$	1.28	0.101

Table 11. Summary of Hypotheses Test Results

Hypothesis statement	**Independent variable**	**Dependent variable**	**Results**	**Table #**	**Model / Equation #**
H1a: CIT has positive short-term effects on *net patient revenue*.	CIT_t	NPR	Supported	5	(1)
H1b: BIT has positive short-term effects on *net patient revenue*.	BIT_t	NPR	Supported	5	(1)
H2a: CIT has positive long-term effects *on net patient revenue*.	$\sum_{s=0} \mathrm{CIT}_{t-s}$	NPR	Supported	6	(1)
H2b: BIT have positive long-term effects *on net patient revenue*.	$\sum_{s=0} \mathrm{BIT}_{t-s}$	NPR	Supported	6	(2)
H3a: CIT has negative short-term effects on the *uncompensated care ratio*.	CIT_t	UCR	Supported	5	(3)
H3b: BIT has negative short-term effects on the *uncompensated care ratio*.	BIT_t	UCR	Not supported	5	(3)
H4a: CIT has negative long-term effects on the *uncompensated care ratio*.	$\sum_{s=0} \mathrm{CIT}_{t-s}$	UCR	Not supported	6	(3)
H4b: BIT has negative long-term effects on the *uncompensated care ratio*.	$\sum_{s=0} \mathrm{BIT}_{t-s}$	UCR	Not supported	6	(4)
H5a: Hospital size interacts with CIT to predict long-term *revenue management performance* such that the positive long-term effects of CIT on *net patient revenue* and the negative long-term effects of CIT on the *uncompensated care ratio* are stronger for larger hospitals	$\sum_{i=0} \mathrm{size} \times \mathrm{CIT}_{t-s}$	NPR & UCR	Not supported	8	(1) & (2)
H5b: Hospital size interacts with BIT to predict long-term *revenue management performance* such that the positive long-term effects of BIT on *net patient revenue* and the negative long-term effects of BIT on *uncompensated care ratio* are stronger for larger hospitals	$\sum_{i=0} \mathrm{size} \times \mathrm{BIT}_{t-s}$	NPR & UCR	Supported	8	(3) & (4)
H6a: Hospital type (profit vs. nonprofit) interacts with CIT to predict *revenue management performance* such that the positive long-term effects of CIT on *net patient revenue* and the negative long-term effects of CIT *on uncompensated care ratio* are weaker for nonprofit hospitals	$\sum_{i=0} \mathrm{nonprofit} \times \mathrm{CIT}_{t-s}$	NPR & UCR	Supported	10	(1) & (2)
H6b: Hospital type (profit vs. nonprofit) interacts with BIT to predict *revenue management performance* such that the positive long-term effects of BIT on *net patient revenue* and the negative long-term effects of BIT *on uncompensated care ratio* are weaker for nonprofit hospitals	$\sum_{i=0} \mathrm{nonprofit} \times \mathrm{BIT}_{t-s}$	NPR & UCR	Not supported	10	(3) & (4)

6 Discussion

Hospitals in the US and other countries seek to balance not only financial objectives, such as providing returns on assets to owners (in the case of for-profit hospitals) and cost efficiency, but also provide social returns in the form of charity care and medical education. Donations and subsidies may cover some of the cost of meeting social obligations, but for most hospitals, these extra resources are inadequate to cover the cost of providing such services. IT can improve hospital performance by allowing the hospital to identify mechanisms to enhance their revenues. These mechanisms include collecting a higher percentage of patient revenues and improving management of the revenue cycle, which can thereby reduce uncompensated care costs. In this paper, we make theoretical arguments and propose hypotheses on the effects of IT investment on revenue management performance and empirically test our hypotheses using various proprietary data sources, finding supportive results.

Our empirical analyses generally support our hypotheses regarding the effect of IT investment on revenue management performance. We find strong support for the hypotheses regarding the effect of IT investment on revenue enhancement and partial support for the hypotheses regarding the uncompensated care ratio. The impact of both clinical and business IT investment on revenue generation is strong and has long-term impacts, implying that IT investment does pay off over the long run. Another important finding regards the learning process that hospitals undergo following the implementation of IT systems. As suggested by many previous IS studies, organizations experience a period of learning and adaptation that is necessary before they can take complete advantage of the newly implemented systems and realize their expected value.

Also, we found that hospital size can be a vital factor in determining how to maximize the efficacy of IT investments. Our findings suggest that larger hospitals are better at utilizing new technologies to facilitate revenue management through both expanding revenue sources and managing sunk costs associated with uncompensated care. We argue that larger hospitals typically possess more and better medical, human, and administration resources, which have greater complementarities with IT investments and contribute to the positive synergistic effects identified between IT investments and hospital size.

It is also worth noting that we only found this moderation effect in relation to business IT investments. We argue that this effect is due to the nature of technology. Larger hospitals typically have larger administrative teams as well as more guidelines and management oversight, which better facilitate the organizational adaptation necessary to complement IT investment. However, larger hospitals also tend to have more experienced and established medical providers, who may be more likely to insist on retaining the status quo and less likely to agree to the changes necessary to accommodate new IT systems. Therefore, while there may be positive interaction effects between hospital size and clinical IT investment, such effects may be offset by negative effects associated with the reluctance to make changes to adapt to the new technologies on the part of the highly skilled and reputable medical staff likely to be employed by larger hospitals.

Finally, our findings indicate that different types of hospitals do not benefit equally from IT investments. Different institutional backgrounds and service missions are associated with different revenue models, which, in turn, impacts hospitals' incentives for participating in revenue management strategies and implementing new IT investments for such purposes. Therefore, nonprofit hospitals may not be as motivated as for-profit hospitals to successfully implement the necessary organizational changes to complement IT investments. Indeed, we found that clinical IT investments benefit for-profit hospitals more than their nonprofit counterparts. The fact that the interaction effect regarding hospital type is present only for clinical IT systems supports our argument regarding organizational learning and adaptation. Since clinical IT systems are more complex and require more process reengineering, medical providers working at nonprofit hospitals may be more reluctant to make changes in their practices to accommodate the new systems. However, given that business IT systems are highly standardized and less dynamic in nature, they thus require less organizational adaptation than clinical systems. The above arguments suggesting that healthcare providers may be reluctant to make the changes necessary to accommodate IT adoptions not only makes intuitive sense but is also supported by a recent study showing that physicians engage in accelerated retirement or job changes to a greater extent when they experience routine disruptions caused by new technology implementations and the associated organizational pressure to adapt to them (Greenwood, Ganju, & Angst, 2019).

This study contributes to the IS and management literatures in many ways. First, it sheds new light on the role of IT for organizational performance, specifically in the healthcare industry. While previous studies have focused on performance measures related mainly to cost or efficiency concerns and healthcare quality, this study examines the important yet understudied metric of revenue management. Since effective revenue management is essential for hospital performance, the context of this study is highly relevant for practice as well as theory. Second, this is the first study that differentiates clinical from business IT and investigates their differential effects on hospital performance. Third, this study confirms the findings of previous literature regarding the complementarities between technology adoption and organizational adaptations and provides another piece of empirical evidence demonstrating that organizations need to reengineer their processes and make ample supporting resources available in order to successfully implement new technologies. There is a learning curve that hospitals must overcome before they can fully assimilate an IT adoption and leverage it to create value in terms of revenue enhancement. Finally, our findings regarding the heterogeneous effects of IT across hospital types and sizes are unique and provide evidence that organizations must all be treated differently and may benefit from IT adoption in different ways and to different degrees.

Our study also provides several managerial implications for healthcare administrators and hospital decision makers. First, although IT generally improves hospitals' revenue management practices, administrators should be aware that IT investment may not pay off immediately. Especially for those implementations involving complex clinical applications that require learning and experience, it may take years for them to start creating measurable value; thus, management teams, board members, medical providers, and administrative personnel should be encouraged to exercise patience and tolerance regarding early struggles and complications involving IT implementations. Finally, managers should recognize that IT implementations may not deliver the same value for all hospitals. Indeed, our findings indicate that IT implementations will yield the most benefit for larger and for-profit hospitals.

7 Limitations and Future Research

We acknowledge two limitations of our study, which, however, offer avenues for further research. First, the use of observational data is inevitably susceptible to endogeneity—particularly endogeneity caused by reverse causality and omitted-varible bias—which makes it difficult for researchers to draw causal inferences. In the context of this study, although we argue that IT investments lead to higher net patient revenue for hospitals, it could also be argued that a hospital is more likely to invest in IT when expected revenues are high, which would indicate a reverse-causality problem. To mitigate reverse causality, in this study, we used the GMM approach, which is a panel regression estimator that specifically aims to prevent bias based on reverse causality. The GMM estimator was developed by Arellano and Bover (1995) and is an extension of the dynamic panel data regression proposed by Arellano and Bond (1991).

Second, this study demonstrates the positive, long-term, combined effect of CIT (and BIT) on net patient revenue. However, we do not illuminate the specific mechanisms used by hospitals to achieve such positive long-term outcomes. This study does not focus on the serial changes in the effect of CIT (and BIT) on net patient revenue. We encourage future research to investigate the specific organizational mechanisms allowing hospitals to realize positive revenue changes. Moreover, our study only covers ten years of data, which may not be enough for a time series (*not* panel data) analysis. For example, in the unit root test for stationarity over time, there are only 30 data points; as such, a potentially low statistical power may be expected. Thus, we encourage future research to use quarterly based data to investigate the effects of such mechanisms.

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