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The Effect of IT Capital on Hospital Efficiency

Michael G. Housman and Lorin M. Hitt
The Wharton School
University of Pennsylvania
Philadelphia, PA
housman@wharton.upenn.edu *lhitt@wharton.upenn.edu*

Kinga Elo and Nicolas Beard
PricewaterhouseCoopers, LLP
Seattle, WA
kinga.z.elo@us.pwc.com *nicolas.beard@us.pwc.com*

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Introduction

The academic literature on hospital information technology is relatively sparse despite its important implications for hospital management, with only limited empirical evidence linking implementation of hospital IT systems with improvements in health care quality, financial and operational performance. While the literature base is expanding, the majority comprises case studies and expert opinion. This study aims to corroborate the observational evidence, using a cost function estimation approach to examine the impact of IT capital investments on hospital cost efficiency. We find that the impact of IT capital on hospital productivity follows a non-linear pattern, indicating that a certain amount of IT investment is necessary before hospitals gain efficiency benefits from that investment. Our approach also enables us to explore the effects of individual IT applications. We find that significant differences exist in the cost-reducing effects of application types. Administrative applications show a shorter term positive effects, while clinical applications need significantly more time to demonstrate their impact.

Consistent with prior work on hospital cost efficiency, we utilize a translog cost function system (the *primal* and the *factor share* equations) to calculate the marginal product of various factor inputs in hospitals (capital, labor materials) as well as IT capital. By adding additional terms to allow for a nonlinear relationship between IT capital and hospital efficiency we can also examine whether the marginal benefits of IT capital depend on the level of investment. In this initial analysis we focus on two simple output measures, inpatient discharges and outpatient visits, although work is underway to adjust these outputs for quality of care.

Previous studies have either utilized cross-sectional analyses or small samples of convenience; instead, we analyze data that includes a majority of US hospitals from 1999 to 2004. Below, we outline the theoretical model that we utilize to describe hospital cost efficiency, the variables included in the model, and the assumptions implicit in our model. We then describe the datasets that we employ and our method of constructing the measure of IT capital. We conclude with a discussion of preliminary empirical results and outline our plans for further research.

Model

The goal of this study is to examine the relationship between IT capital stock and cost efficiency in US hospitals. Following the existing literature on IT productivity, we estimate a hospital production function using a longitudinal firm-level dataset. We model the production process as relating ordinary capital stock (K), labor (L), materials (M), and IT capital (IT) to hospital output (Y) as represented by discharges and outpatient visits. In accordance with the literature, we use the dual cost form of the production function since this approach avoids having to identify a single output measure. Calculation of factor prices follows the conventional approach in this literature (Zuckerman, et al., 1994; Rosko, 2001).

With respect to the choice of a functional form for our production function, we follow the example of prior research in the field and utilize a translog function (Christensen, et al., 1973; Berndt, 1990). The translog function is appropriate here because of its flexibility, minimal set of assumptions, and the fact that it permits us to calculate cross-elasticity effects. Within our cost function, IT and capital are treated as quasi-fixed inputs and treated as fixed in the short run. While it may initially appear unusual to treat capital as fixed in the short run, we felt that this was an appropriate assumption within the hospital industry because our measure of capital (revenue adjusted bed size) is less easily adjusted than traditional forms of capital (Brown & Christensen, 1981)[1]. Results were obtained by solving the following system of equations:

$$\begin{aligned}(1)\qquad \ln\frac{VC}{P_M} = {} & \alpha_0 + \beta_W \ln\frac{P_W}{P_M} + \sum_Y \beta_Y \ln Y + \beta_K \ln K + \beta_{IT} \ln IT + \frac{1}{2}\beta_{WW} \ln^2 \frac{P_W}{P_M} + \frac{1}{2}\sum_Y \beta_{YY} \ln^2 Y + \\ & \frac{1}{2}\beta_{ITIT} \ln^2 IT + \frac{1}{2}\beta_{KK} \ln^2 K + \sum_Y \beta_{YW} \ln Y \ln\frac{P_W}{P_M} + \beta_{ITW} \ln IT \ln\frac{P_W}{P_M} + \beta_{KW} \ln K \ln\frac{P_W}{P_M} \\ & + \sum_Y \beta_{ITY} \ln IT \ln Y + \beta_{ITK} \ln IT \ln K + \sum_Y \beta_{YK} \ln Y \ln K + \sum_j \beta_j Z_j\end{aligned}$$

where P_W represents wages and P_M represents material costs. Our production function represented in equation (1) was solved in conjunction with the labor and material share of operating costs represented in equation (2):

$$(2)\qquad S_L = \frac{P_W L}{VC} = \alpha_0 + \beta_W \ln\frac{P_W}{P_M} + \sum_Y \beta_Y \ln Y + \beta_{IT} \ln IT + \beta_K \ln K$$

[1] In our model, adjusting bed size by revenue produced more reasonable estimates of hospital capital. So we have used this measure of capital in our model but tested the model using unadjusted bed size and it produces no appreciable difference in the results.

where S_L represents the labor cost share and S_M represents the material cost share in total operating costs such that $S_L + S_M = 1$. In our model, the production function is assumed to be linearly homogenous in the variable labor and material costs. This is a standard assumption.

Data

The statistical analysis seeks evidence of relationships between levels of IT capital and hospitals' efficiency. The data used in the analysis come from two primary sources. The HIMSS Analytics (formerly Dorenfest 3000+) database maintains survey data on information technology applications in over 1,100 integrated healthcare delivery systems (IHDS's) and 4,000 hospitals throughout the U.S. The HIMSS Analytics database provides usable and consistent data from 1999 through 2004 on a total of 40 software applications was available from 1999 to 2004 and have been included in the analysis[2]. 28 of these applications were classified by an expert as being 'administrative' in nature and 12 were considered to be 'clinical' applications.

In order to calculate the level of IT capital stock in sampled hospitals, an expert provided cost estimates for each application type within a representative 600-bed hospital, based on real price proposals from several software companies that were adjusted for hospital size.

Data from HIMSS Analytics was merged by hospital Medicare ID numbers with data from Solucient's ProviderView database, which was derived from Medicare Cost Report (HCRIS). This database, released annually, maintains information on demographics, utilization, productivity, and expenses for nearly all hospitals in the U.S. Solucient ProviderView enabled the calculation of resource use (FTE employees, materials, capital), resource costs (wages, material costs, capital costs), output (discharges, surgical operations and emergency room visits), heterogeneity of outputs (case mix), hospital demographics (geographic location, teaching status, profit status, ownership, medical school affiliation), and total operating expenses. Table 1 of this abstract compares the demographic characteristics of our final sample with the entire population of US hospitals. Our dataset is constrained by the survey strategy employed by HIMSS Analytics, which tends to over-sample larger hospitals while under-sampling government hospitals. Table 2 presents descriptive statistics for the variables representing productive inputs and outputs that we employ in our model.

[2] Survey data for 2 of these 40 software applications was first collected in 2000 (rather than 1999). These values were imputed backwards from 2000 to 1999 in order to fill in the data gaps and include as many software applications as possible in the study.

Preliminary Results and Discussion

Table 3 at the end of this abstract presents the results of our analysis. The required regularity conditions for a well-behaved cost function are satisfied in our analysis. The symmetry and homogeneity of degree one in factor prices restrictions that were imposed on our system are verified as the system meets the monotonicity, non-negativity, and concavity conditions (Berndt, 1991). Monotonicity was satisfied because the estimated marginal cost of labor is positive. As the predicted cost shares of labor are positive, the non-negativity conditions were also satisfied. The second order derivatives of labor are all non-positive, indicating that strictly quasi-concavity of input prices is also satisfied.

The coefficient on wage is positive as expected, implying that production costs increase as the value of input increases. The parameter estimate of the output measures (discharges, surgical operations and emergency room visits) are also positive confirming that the cost function is well behaved and specified. The positive signs indicate that an increase output increases hospital costs. Overall, this suggests that our baseline estimates are reasonable.

The results suggest that higher levels of in IT capital are associated with reduced short-term operating costs in acute care hospitals, only after a threshold level of investment has been reached. Figure 1 depicts operating costs initially rising steeply with increasing IT capital, leveling off at a ‘tipping point’, and then gradually decreasing at higher levels of IT capital. We also find that non-profit hospitals appear less efficient than for-profit hospitals in terms of their IT usage, reaching the tipping point at higher levels of IT capital.

This concave relationship between IT capital and total operating costs is consistent with our expectations. We believe that initial increases in IT capital may entail significant ‘start-up’ expenses (networking infrastructure, recruitment of IT staff) which increase costs despite any efficiency gains that the IT applications might provide.

To further examine this relationship, we split IT capital into its ‘administrative’ and ‘clinical’ components. Administrative applications show efficiency gains, even at relatively low levels of IT capital investment, with a higher marginal gain in for-profit hospitals. Clinical applications show no efficiency gains in non-profit hospitals: increasing levels of clinical IT do not lead to operating cost savings. They do appear to improve efficiency in for-profit hospitals.

We also examined the impact of these applications across different time horizons. Clinical applications do demonstrate efficiency gains in non-profit hospitals over longer periods of time. In for-profit hospitals, clinical applications also yield both short- and long-term gains. Administrative IT applications show a strong positive efficiency effect in both the short- and long-term within for-profit and non-profit hospitals.

Our expert further subdivided the ‘administrative’ and ‘clinical’ applications into smaller categories. Among administrative applications, base administrative and financial applications (e.g., billing, eligibility, staffing, etc.) have the highest marginal effect on efficiency. Medical record applications (e.g., abstracting, chart tracking/locator, etc.) generally do not show efficiency gains in non-profit hospitals. Financial decision support (e.g., clinical decision support, flexible budgeting, etc.) applications show efficiency improvements only in for-profit hospitals.

Among clinical applications, ancillary departmental applications (e.g., laboratory, radiology, etc.) yield efficiency gains in for-profit hospitals and long-term efficiency gains in non for profit hospitals. Clinical departmental applications (e.g., cardiology, surgery, etc.) on average show efficiency gains in both non-profit and for-profit hospitals. Enterprise clinical applications (e.g., clinical documentation, order communication/results, etc.) generally show efficiency improvements in both non-profit and for-profit hospitals in the short- and long-term.

These results fill in a substantial gap in the existing literature by demonstrating the link between IT capital stock and efficiency gains in health care settings. Our unique dataset in conjunction with the methods we employ overcome many of the shortcomings of previous work in this field. There remain several extensions to this work that we intend to explore. In our final paper, we plan on adjusting these estimates to account for differences in mortality rates, as a rough proxy for the quality of services provided. Additionally, we hope to pursue a follow-up project that examines the direct link between IT implementation and health care quality, as measured through a variety of patient safety indicators beyond estimates of patient mortality.

References

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Table 1. Descriptive Statistics for the Study Sample and Population of US Hospitals

	Hospital Sample 3,416 hospitals		Hospital Population 6,072 hospitals	
	Number	**Percent**	**Number**	**Percent**
Hospital Beds:				
Less than 50 beds	403	11.80%	1,690	27.83%
Between 50 and 100 beds	538	15.75%	1,341	22.08%
Between 100 and 200 beds	1,132	33.14%	1,390	22.89%
Between 200 and 300 beds	594	17.39%	728	11.99%
Between 300 and 400 beds	338	9.89%	396	6.52%
Between 400 and 500 beds	168	4.92%	210	3.46%
Greater than 500 beds	243	7.11%	317	5.22%
Geography:				
Eastern hospitals	599	17.54%	951	15.66%
Western hospitals	969	28.37%	713	11.74%
Southern hospitals	1403	41.07%	2637	43.43%
Midwestern hospitals	445	13.03%	1771	29.17%
Profit/Ownership Status:				
For-profit hospital	549	16.07%	1,206	19.86%
Non-profit hospital	2,323	68.00%	3,181	52.39%
Local government hospitals	544	15.93%	1,443	23.76%
Federal government hospitals	0	0.00%	242	3.99%

Table 2. Summary Statistics for Input and Output Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
opex	9760	147836.6	145820	2288.2	1890924
NFP[1]	10067	0.809	0.393	0	1
IT	8169	10.046	0.281	8.11	11.05
discharge	10067	3962.4	2991.9	2.75	34940.68
wage	10042	43.491	21.353	0	952.170
capital	9865	238.012	169.014	10	1673.205
vtot	10049	41390.27	27598.93	9	319662
coth	10061	0.112	0.315	0	1
med_school	10061	0.360	0.480	0	1
casemix	10067	1.424	0.236	0.6199	3.015589
lurban	10067	0.596	0.491	0	1
dispr	10067	0.304	0.460	0	1

[1] FP – for-profit; NFP – not-for-profit

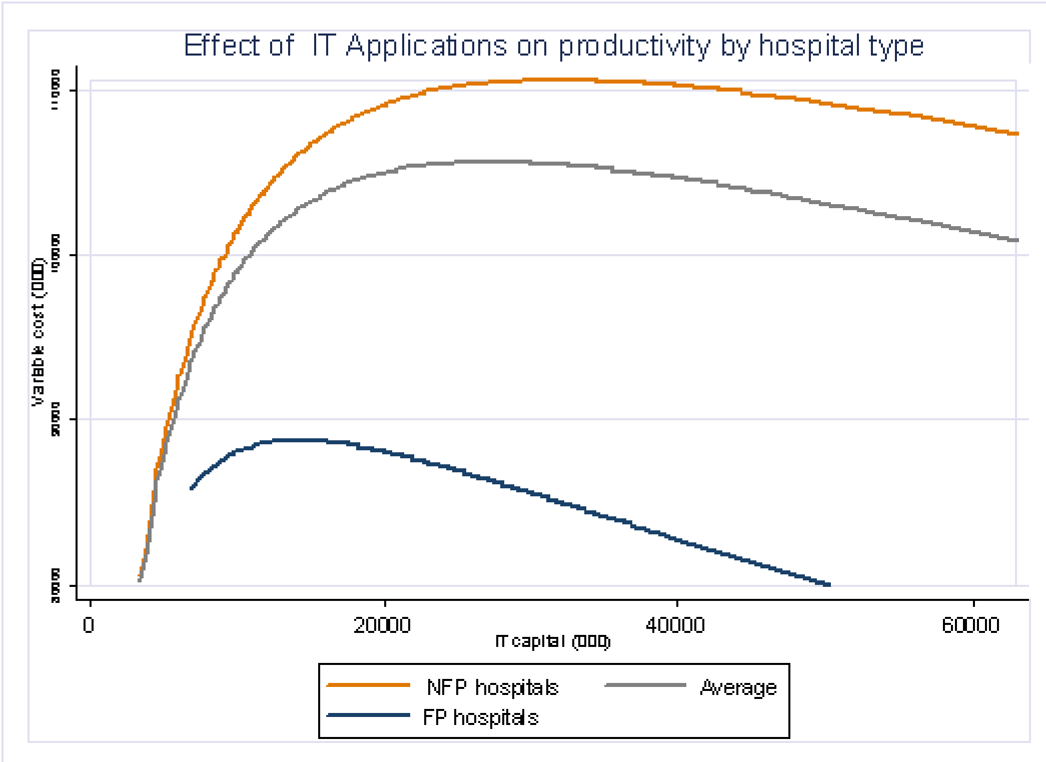
Table 3. Effect of Total IT Capital Stock on Efficiency

Equation	Obs	Parms	RMSE	R-sq	chi2	P
lopex	7867	80	0.237	0.936	1.84E+07	0.000
SL	7867	63	0.060	0.783	404462.64	0.000

	Coef.	Std. Err.	z	P>|z|
lopex				
NFP[1]	-0.999	0.286	-3.5	0.000
FP_IT	-0.105	0.028	-3.7	0.000
lvtot_IT	-0.024	0.022	-1.1	0.271
IT	0.997	0.535	1.86	0.062
IT2	-0.128	0.057	-2.25	0.024
ldischarge~T	-0.045	0.025	-1.82	0.069
lwage_IT	0.026	0.016	1.64	0.102
lcapital_IT	0.070	0.031	2.29	0.022
lwage_lcap~l	-0.126	0.012	-10.73	0.000
lwage_ldis~e	-0.104	0.009	-10.9	0.000
lwage_lvtot	0.061	0.006	9.75	0.000
lcapital_l~t	-0.006	0.013	-0.44	0.657
ldischarge~t	-0.029	0.011	-2.67	0.008
ldischarge~l	-0.242	0.015	-16.41	0.000
lvtot2	0.086	0.007	12.67	0.000
lwage2	0.186	0.008	23.27	0.000
ldischarge2	0.189	0.012	15.2	0.000
lcapital2	0.334	0.026	12.67	0.000
ldischarge	2.280	0.236	9.65	0.000
lwage	0.173	0.170	1.02	0.307
lcapital	-1.224	0.288	-4.25	0.000
lvtot	0.035	0.215	0.16	0.870
coth	0.108	0.011	9.71	0.000
med_school	0.079	0.007	11.07	0.000
casemix	0.345	0.018	19.46	0.000
lurban	0.057	0.006	8.89	0.000
dispr	0.023	0.008	2.95	0.003
SL				
lvtot	0.018	0.002	11.98	0.000
IT	-0.013	0.003	-4.22	0.000
lwage	0.132	0.001	96.33	0.000
lcapital	-0.015	0.002	-6.61	0.000
ldischarge	-0.011	0.002	-6.23	0.000
coth	0.030	0.003	11.38	0.000
med_school	0.013	0.002	7.54	0.000
casemix	0.008	0.004	1.73	0.084
lurban	-0.020	0.002	-12.53	0.000
dispr	-0.006	0.002	-3.18	0.001

[1] FP – for-profit; NFP – not-for-profit

Figure 1. Effect of IT Capital Stock on Efficiency by Hospital Type



[1] FP – for-profit; NFP – not-for-profit