

Productivity of Information Systems in the Healthcare Industry

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This research paper analyzes the impact of information technology (IT) in a healthcare setting using a longitudinal sample of hospital data from 1976 to 1994. We classify production inputs into labor and capital categories. Capital is classified into three components—medical IT capital, medical capital, and IT capital—and labor is classified into two components, medical labor and IT labor. Results provide evidence that IT contributes positively to the production of services in the healthcare industry.

(Organizational Productivity; Health IS; IS Investment; IS Performance Evaluation; IS Research Methodology)

1. Motivation

Organizations, convinced that information technology (IT) provides business value, have been acquiring increasing amounts of IT capital over the past two decades. The average amount of IT investment varies considerably by industry. The healthcare industry, for example, has implemented IT relatively slowly. Only in the last few years have hospitals invested heavily in IT (Kettelhut 1992). Tremendous national interest in healthcare costs (Fuchs 1996) and conflicting results from IT productivity studies in other industries (e.g., Brynjolfsson and Yang 1996) motivate our study of the value created by IT in the healthcare industry.

Data for the study were obtained from the Washington State Department of Health. These regulatory data offer several advantages. First, hospitals are required to report accounts for IT expenses separate from other capital. Prior studies have relied on ex ante surveys for IT expense data, and this information may not be accurately reported. Second, it is difficult to draw meaningful inferences from empirical studies using data sets

that contain observations from heterogeneous firms. The use of one industry (hospitals) increases our ability to control for key organizational and environmental confounds. Furthermore, cost information used by other researchers includes allocations of headquarter expense. Allocations do not reflect actual resource usage and thus lower the quality of data. Our dataset does not suffer from these shortcomings. Accordingly, we explore the productivity issue (the enhancement of output for a unit change in input) of IT using a high-quality data-set from a cost-conscious industry, and apply a robust model and appropriate behavioral assumptions for hospitals.

We classify hospital capital into three components: IT capital, medical capital, and medical information technology capital. IT capital includes data processing and communication capital (mainly for administrative purposes). Medical information technology capital includes equipment used for diagnosis and therapeutic purposes, i.e., to collect data from patients or report information to medical personnel (e.g., X-ray

machines, magnetic resonance imaging, etc.). Medical capital consists of equipment used solely for therapeutic purposes (e.g., improvements in acute care wards, or lasers). Labor is classified into two components, medical and IT labor. Productive capital is calculated as capital stock aggregated over the past several years using annual capital expenses. The validity of the capital stock measure requires a time window over the life expectancy of capital input at a minimum. Accordingly, we use an 18-year window (relatively long compared to prior research).

The methodology adopted for this study is also different from previous IT productivity studies. We use a state-of-the-art parametric technique, the stochastic frontier approach. Since this approach assumes all production processes are inherently inefficient, the model parameters capture inefficiencies of the production process at the firm level (Lovell 1993). In addition to these research refinements, this paper adds to the existing literature in several ways. First, there is little research investigating the productivity of IT investments in the healthcare industry. Since the adoption of IT in the healthcare industry coincided with the transition to for-profit ownership and the pressure of cost control from managed care and the government, measurement of the business value of IT investment has important managerial implications for practitioners. Second, our derivation of input and output variables is more robust than in prior research (for example, the use of capital stock rather than annual capital expense). Last, capital investment is categorized into three types, providing a more refined partitioning than prior studies.

The paper is organized as follows. In the next §, the healthcare industry is briefly reviewed, and research expectations are described. In § 3, production theory and empirical models are described. Section 4 describes the data. Results are presented in § 5, and § 6 summarizes and concludes our study.

2. Background

The unit of analysis in this study is a hospital. The hospital industry differs from other industries in ways that may impact the use of IT. These include the following: (1) Hospital organizational structure consists of two separate entities. The medical staff governs

medical decision making, and hospital administrators provide services that physicians require to treat patients (Harris 1977). This creates a tension between physicians, who would prefer acquisition of the latest medical technology, and administrators, who prefer to acquire capital such as IT for administrative purposes. (2) The environment is highly regulated. Government legislation determines the amount and method of hospital reimbursement for large portions of patient care and thus affects hospitals' economic behavior (cost minimization, revenue maximization, etc.) (Sloan et al. 1988).

The healthcare industry was relatively slow in adopting information technology. Hospitals emphasized revenue maximization prior to 1983, thus patient billing systems were among the early uses of IT. Patient charges were delivered daily to data processing so that patient bills were current and could be issued at discharge. Mainframe systems were primarily used for billing and general ledger activities. Smaller hospitals continued to perform these functions by hand. Information technology was also used intensively for regulatory reporting purposes, including budgeting. After the change in Medicare reimbursement in 1983, IT continued to be adopted for revenue enhancement. Sophisticated software allocated costs with the objective of increasing revenues from third-party payers such as Medicare (Zimmerman 1995). Personal computers were increasingly used by individual departments for specific purposes such as inventory control in pharmacies. Automating clinical records is a relatively new objective for hospitals (Hern 1996). Only in recent years have hospitals attempted to develop integrated cost accounting systems (Andrianos and Dykan 1996).

Over the past 30 years, there has been a considerable amount of work on the productivity of healthcare organizations. The search for a quantitative measure of the contribution of the various input factors to production has led to the estimation of production functions and frontiers using parametric and nonparametric techniques (e.g., Grosskopf et al. 1995).

Research Expectations. (1) Hospitals were slow to adopt IT. During the early sample years, investments in IT capital and labor are proportionately low when compared to total investments. Therefore we expect

low average IT productivity over the entire time period. (2) In a rapidly changing reimbursement environment, especially after 1983, hospitals lacked direction in employing IT and overhauled their systems frequently (Palley and Conger 1995). Thus low productivity for IT labor is expected. (3) Federal and state regulatory limits on investment in expensive medical information technology are expected to result in high productivity of medical information technology for the few hospitals allowed to invest. (4) To minimize costs, hospitals attempt to schedule medical labor to meet demand. Accordingly, we predict a positive (and potentially the largest) productivity effect for medical labor.

3. Production Theories and Productivity Analysis

Prior IT productivity studies have been based on the theory of revenue maximization with the additional assumption of exogenously determined input expenditures. However, empirical analysis of production models requires appropriate assumptions about firms' economic behavior including *cost minimization*, *profit maximization*, and *revenue maximization*. If the regression model fails to include managerial decision-making information (e.g., managers' use of estimated demand and input factor prices), the estimates of the production function parameters cannot be usefully interpreted. The use of behavioral assumptions in productivity analysis differs markedly from these simple regression models. Whereas a regression model examines the existence of correlation between independent and dependent variables, a behavioral model attributes causality to such correlation.

Incorporating the Behavioral Assumption. The behavioral model most commonly ascribed to hospitals is cost minimization (Sloan et al. 1988). Consider a cost minimization behavioral model given by

$$\begin{aligned} \min_{\bar{z}} \quad & \bar{w} * \bar{z} \\ \text{s.t.} \quad & \bar{y} = f(\bar{z}), \end{aligned} \quad (1)$$

where $\bar{w} = (w_1, \dots, w_n)$ is the vector of n input prices; $\bar{z} = (z_1, \dots, z_n)$ is the vector of inputs (such as capital and labor categories); $\bar{y} = (y_1, \dots, y_m)$ is the vector of

outputs (such as number of inpatients cared for); $f(\bar{z})$ is the correspondence¹ that defines the production technology; and $f(\bar{z})$ quantifies the feasible outputs that can be produced from given quantities of inputs \bar{z} .

Input quantities are assumed to be the decision variables (endogenous), and input prices and output quantity are assumed to be exogenous. The output in hospitals is exogenous because the amount of service provided by a hospital is determined by the casualty and illness rates in the population (McClellan 1995). While hospitals have some degree of control over discharge dates for patients, they have relatively little control over the demand for services. The first-order conditions for Equation (1) combined with the production function $f(\bar{z})$ yields the following system of equations:

$$\bar{y} = f(\bar{z}) \quad (2)$$

$$\frac{f_i(\bar{z})}{f_j(\bar{z})} = \frac{w_i}{w_j} \quad \forall i, j = 1, \dots, n, i \neq j, \quad (3)$$

where $f_k(\bar{z})$ refers to the partial of $f(\bar{z})$ with respect to z_k . Equations (2) and (3) represent a set of n equations, one equation for the production function and the second set containing $n - 1$ equations. The microeconomic intuition here is that, in equilibrium, a firm will equate the ratio of marginal product of an input and its price for all input factors to a common ratio. Using suitable functional forms for $f(\bar{z})$, the generic system of equations given above can be written explicitly in terms of the parameters of the production correspondence.

Several factors (e.g., bounded rationality, organizational constraints, and mismanagement) prevent the assurance of first-order cost minimization in an exact manner in empirical data. To reflect this, we use stochastic production frontiers to introduce inefficiency terms into the equations. That is, Equations (2) and (3) are rewritten with the stochastic inefficiency terms (Schmidt and Lovell 1979) as follows.

$$\bar{y} = f(\bar{z})e^{(v-u)} \quad (4)$$

$$\begin{aligned} \frac{f_i(\bar{z})}{f_j(\bar{z})} &= \frac{w_i}{w_j} e^{\varepsilon_k} \quad \forall i, j = 1, \dots, n, k = 1, \dots, \\ &n - 1, \text{ and } i \neq j, \end{aligned} \quad (5)$$

¹ $f(\bar{z})$ is called the production function when \bar{y} is single-valued and not a set.

where u is the technical inefficiency of a firm, v is random statistical noise, and ε_k is the relative allocative inefficiency for inputs i and j . Note that there are $n - 1$ allocative inefficiency factors since there are n input factors and $n - 1$ allocation equations.

Once the production function is estimated, the impact E_i of any input z_i is determined by simply differentiating the function $f(\bar{z})$ with respect to the input factor z_i . That is,

$$E_i = \frac{\partial p_y f(\bar{z})}{\partial p_i * z_i} \quad (6)$$

Equations (4) and (5) present a realistic picture of hospital operations by explicitly modeling two factors. First, it is unlikely that any two hospitals will produce the same levels of output using identical levels of input such as IT resources. The parameter u_k (such that $u_k > 0$) reflects technical inefficiency, which is the difference in converting inputs to outputs between firm k and the "ideal" (see Equation (4)). Second, factors such as bounded rationality, as mentioned above (see Equation (5)), prevent firms from allocating resources at the optimal level given by the first order condition of cost minimization. The allocative inefficiency, ε_k , measures the difference between the actual allocation and the optimal allocation.

The Full Information Maximum Likelihood (FIML) method of estimation is applied on the maximum likelihood expression derived from the system of equations given above to yield consistent and most efficient estimates of the parameters (Greene 1993 p. 612).²

4. Characteristics of the Data Set

Data from one state are used to eliminate systematic biases resulting from accounting practices and health-care policies peculiar to different states. The financial data collected by the Washington State Department of Health consist of 83 accounts from three types of departments: (1) those for inpatient care, primarily the room and board functions, e.g., acute care and intensive care; (2) ancillary departments that provide services for both inpatients and outpatients, e.g., emergency room and X-ray lab; and (3) cost centers that

provide services such as admitting and data processing.

These data include charges and costs. Charges are the total dollars billed for patient services during the period and do not reflect reimbursement. Costs are the accumulated operational expenses for the period. The cost information includes detailed expense categories such as salaries and wages, supplies, and rent.

We asked hospital managers to classify capital into categories according to our definitions. Capital expenses allocated to data processing, data communication, medical records, admitting, central service, purchasing, accounting, medical records, and personnel are categorized as IT capital. The capital expenses allocated to MRI, CT Scan, radiology (diagnostic), radiology (therapeutic), electrodiagnosis, nuclear medicine, emergency room, electromyography, recovery room, anaesthesiology, IV therapy, and surgical service are considered medical IT capital. Capital expenses in accounts such as ICU, semi-intensive care, acute care, physical rehabilitation, laboratory, pharmacy, home care services, and medical staff are classified as medical capital. Several of the remaining accounts (dietary, cafeteria, laundry, etc.) include negligible capital expense, either due to few capital expenses or because these are outsourced.

Any capital expense in these remaining accounts is considered structural capital and is added to medical capital. Salaries in IT accounts are classified as IT labor, and salaries in the remaining accounts are classified as medical labor. For the output measure, we use adjusted patient days, which is the sum of inpatient days and "outpatient days." Outpatient days are derived by dividing outpatient revenue by inpatient revenue per day (inpatient revenue divided by inpatient days).³

Our sample consists of observations from hospitals classified by the American Hospital Association as general medical and surgical hospitals. We eliminate specialized hospitals such as psychiatric and substance

²Because of the high efficiency of the estimates, FIML typically yields high t-statistics when compared to least-squares methods.

³MacLean and Mix (1991) provide evidence that hospital productivity is underestimated if inpatient and outpatient services are not both included in the output measure. Since our methodology allows specification of only one output, we use revenue shares of the two outputs to weight them prior to aggregating them.

abuse treatment centers. Missing values for capital depreciation are interpolated since the capital stock calculations for each year depend on the capital depreciation amount for previous years and missing values in the series underestimate the derived capital stock. Approximately 30 data points are generated by interpolation. Observations with coding errors are eliminated, leaving approximately 50+ hospital observations per year for the years 1976 to 1994 for a total of 1,064 observations. A statistical description of the sample is presented in Table 1. Means are larger than medians, indicating fewer large hospitals and more small rural hospitals, which is a typical pattern in Western states.

4.1. Measurement of Input and Output Variables

Labor input quantities are available from the full-time equivalent employee measure in the data-set. Since labor data are also available in dollar amounts, the price of labor can be derived for individual hospitals for each year. Salaries are deflated by the employment price index for health care services (Bureau of Statistics 1995) to adjust for quality changes in labor over the years.

Similarly, dollar amount and quantity for the output measure are available in the data. A hospital's annual charges for services (in dollars) reflect the output dollar measure. To adjust for macroeconomic effects over the years, the charges were deflated by the consumer price index for health care services (WEFA 1994). Our previous discussion on production functions suggests

that production functions can be empirically determined only if input quantities \bar{z} are known; dollar amounts (or expenditure) of input factors alone will not suffice. Therefore, in addition to the capital stock in dollar amounts, we also determine the prices of inputs; capital stock and prices will then yield the input quantities.

4.2. Calculation of Capital Stock

We define capital stock as the capital accumulated by the firm from past and current investments, adjusted for depreciation. Capital stock operationalizes the capability of firms' productive assets, whereas annual investments only reflect assets acquired during a particular year. Hence, productive capital stock in a firm is measured by

$$C_t = C_{t-1} + NI_t - D_t \quad (7)$$

where C_t , capital stock in the current year t , is equal to capital stock of the previous year C_{t-1} augmented by new capital purchased in the current year NI_t , and reduced by some portion D_t of capital that has been "retired" or depreciated.

The capital for each account in our dataset is the depreciated dollar amount rather than new annual investment. To convert the depreciated capital data back into capital stock, we assume an appropriate common depreciation rate for all hospitals, since financial depreciation used by individual hospitals does not reflect the actual economic depreciation.⁴ We selected three different series of depreciation rates from the WEFA (1994) data set for the three capital stocks. To reflect technological advancements, a "quality" adjustment was applied by WEFA in preparing these depreciation rates. These series are used extensively by macroeconomists and government agencies such as the Bureau of Labor Statistics. Table 2 lists the capital stock and the series name as described in the WEFA 1994 data set.⁵

Table 1 Descriptive Statistics for the Sample for 1992 (Dollars in Thousands)

Variable	Obs.	Mean	Median	Standard Deviation
Available Beds	55	190	171	138
Adjusted Patient Days	55	56,895	50,454	46,074
Operating Revenues	55	\$66,686	\$52,417	\$58,807
Operating Cost	55	\$63,345	\$44,117	\$61,067
Operating Income	55	\$3,341	\$3,235	\$13,267
IT Capital Expense	55	\$1,137	\$615	\$1,487
IT Labor	55	\$4,449	\$3,071	\$4,253
Medical IT Capital	55	\$1,103	\$763	\$9,907
Medical Capital Expense	55	\$2,805	\$2,008	\$2,672
Medical Labor	55	\$27,458	\$20,687	\$25,227

⁴For example, if \$100 was invested in capital in 1981, then, with a depreciation rate of 20%, the data set would contain \$20 for each year from 1981 to 1985. Capital purchased in 1981 is worth \$0 in 1986, but this capital (plant or equipment) is likely used in the production process after 1985.

⁵We acknowledge that the use of these average series could lead to some bias. However, values of depreciation rates for medical capital range from 0.07–0.1 and since medical capital contains structures

Table 2 Description of Depreciation Rates Used for Capital Stock

Capital Stock Type	Series Description According to WEFA 1994
IT Capital	Annual depreciation rate, nonresidential, producers' durable equipment, information processing equipment
Medical IT Capital	Annual depreciation rate, nonresidential, producers' durable equipment, industrial equipment
Medical Capital	Annual depreciation, producers' durable equipment, other

Appendix A presents the derivation of the productive capital stock from the depreciation rates and the depreciated capital data. Since depreciated capital amounts prior to 1975 are not available, capital stock values for the beginning few years may be "noisy." For sensitivity analysis, we left out the first year and reran the analysis. Similarly, we left out the first two years, and so on, through the first six years. The results were statistically very similar, suggesting that the capital stock stabilized quickly in the successive years (Menon et al. 1997).

4.3. Prices and Quantities of Input Factors

Prior healthcare productivity studies have used input price proxies such as capital divided by number of beds (Zucherman et al. 1994) because data on prices are rarely available. Such price proxies are not adequate for our data since the quantity of capital in the production function would then be determined by number of beds. Alternatively, had we specified individual pieces of equipment as inputs, the model would be intractable. Another approach is to specify categories of capital in terms of abstract and aggregate physical units by first determining the "implicit rental price" or "user cost" of capital. This cost combined with the derived capital stock in dollar amounts yields the

and equipment of lower depreciation, this seems reasonable. The values of depreciation rates for medical IT capital are 0.13–0.17 and IT capital ranges from 0.14–0.19, suggesting more rapid depreciation and obsolescence compared to medical capital. This also seems reasonable.

physical units of capital. The intuition behind such a price derivation is that, at the margin, "the purchase price of a capital asset equals the discounted value of the stream of services (and, hence, implicitly the rents) that the asset will provide" (BLS 1983) and thus reflects the marginal willingness to pay for the asset. The rental prices for input factors rely upon the Christensen and Jorgenson (1969) macroeconomic formulation for asset pricing given below. Ignoring inflation and taxes, the rental price is given by

$$p^t = q^t(r^t + d^t) \quad (8)$$

where q^t is the price index of the asset for the year t , r^t is an annual rate of return on the asset, and d^t is the annual economic depreciation rate. Since the individual asset rate of return is unknown, we use firm i 's rate of return r_i^t in Equation (8) for each asset. The rate of return (Christensen and Jorgenson 1969) for a hospital i in year t is

$$r_i^t = \frac{(I_i^t - \sum_{A=1}^3 [q_A^t * d_A^t * C_{iA}^t - (q_A^t - q_A^{t-1}) * C_{iA}^t])}{\sum_{A=1}^3 [q_A^{t-1} * C_{iA}^t]} \quad (9)$$

where A is the capital category, I_i^t is capital income defined by revenues minus operating expenses, and C_{iA}^t is capital stock in asset A for the unit i for the year t . Annual operating expense is the sum of annual capital depreciation (not capital stock), salaries, supplies, and rental/lease expenses. Price indices q_A^t and rates of depreciation d_A^t are obtained from WEFA (1994). The estimated rate of return is substituted into Equation (8) to yield the rental price of each asset for each hospital year. The above derivation holds theoretical appeal because the rate of return varies over assets, hospitals and years, thereby leading to a set of seemingly exogenous prices.⁶

We assumed that prices vary between hospitals for

⁶Although the dependence between price and capital stock is highly nonlinear, we analyzed their correlation and found low correlation (≤ 0.30). In addition, results from the Hausman specification test support our assumption that the variation in prices mimics exogeneity (Menon et al. 1997).

several reasons. First, although Medicare's flat fee per-diagnosis reimbursement is based on national average resource usage, the reimbursement scheme contains differential payments for teaching hospitals, for hospitals in rural and urban locations, and for hospitals that provide disproportionately large amounts of indigent care. These hospital characteristics provide "unavoidable or legitimate cost differences" (Sheingold 1986, p. 7). Second, our derivation of aggregated capital values combines different types, models, and vintages of similar equipment sold by different vendors resulting in varying prices for a common denomination/unit of capital across the sample. We analyzed the standard deviations of derived prices to see if they varied from hospital to hospital over the years and found that while the mean prices of the three types of capital declined over the years, the variation between hospitals each year was sufficient to mimic exogeneity, but at the same time, did not seem artificially inflated (Menon et al. 1997). Finally, the annual input quantities for capital for each hospital are determined by dividing the capital in dollar amounts by the derived prices.

4.4 Control Variables

Although our data set consists of seemingly homogeneous units, organization-specific factors may give rise to potential confounds. In hospitals, ownership structure, the effect of time, and teaching status need to be controlled for. In this data, ownership is not a confound because the majority of hospitals in Washington are nonprofit (about 92%). However, a control is added for the effect of time since the sample period is 18 years and characterized by technology advances and state and federal policy changes. A dummy variable for teaching status is also included.

5. Results and Discussion

The Cobb-Douglas function represents a constant returns-to-scale production technology and is given by a multiplicatively separable function between the output and input factors as shown below.

$$y = \left(\prod_{i=1}^n z_i^{a_i} \right) e^{bt} e^{cD} \quad (10)$$

where the n input factors are z_i and a_i , and b and D are

parameters that characterize the production function. We do not assume constant returns to scale since that may be too restrictive in the healthcare context. The effect of time is controlled by the variable t and its nonzero coefficient b . The parameter for the teaching dummy D is c .

Substituting Equation (10) into Equations (2) and (3) results in a system of equations. Incorporating the stochastic parameters into these equations, the system can be written in logarithm form as

$$\begin{aligned} v - u &= \log(y) - \sum (a_i \cdot \log z_i) - b \cdot t - c \cdot D \\ \varepsilon_k &= \log(a_1) - \log(a_j) + \log(z_j) - \log(z_1) \\ &\quad + \log(w_j) - \log(w_1), \quad k = 1, \dots, n-1; \\ &\quad j = 2, \dots, n; \quad i = 1, \dots, n. \end{aligned} \quad (11)$$

The above equations cannot be estimated using normal simultaneous equation estimation because two random variables are summed in the first equation in (11). However, Schmidt and Lovell (1979) show that the likelihood function can be obtained with appropriate assumptions regarding the error distributions. See Appendix B for the likelihood function.

To achieve convergence of the likelihood function (Equation (12)), the maximum likelihood function is "concentrated" with respect to the mean and standard deviation of the error terms. The deterministic formulation given by Equations (2) and (3) are first estimated using the FIML/2SLS method on the system of simultaneous equations. The error terms of Equation (3) are calculated using the deterministic formulation estimation. Keeping the mean and standard deviations of errors constant, the maximum likelihood estimates for the stochastic formulation (Equation (12)) are then obtained. These parameter estimates are inserted into Equation (3) and new estimates for the mean and standard deviation of errors are calculated. This procedure is iterated several times until the parameter estimates converge to the .01% level. The results of the stochastic frontier parameter estimation given by Equations (4) and (5) are presented in Table 3.

The results of this analysis support our expectations of high productivity impact for medical IT capital and low average productivity of IT capital. However, the expectation that IT labor would exhibit low productivity impacts (because of frequent overhauling of IT) is

not supported. Table 3 shows that most inputs, including IT labor and capital, exhibit a positive influence on the production of output. Medical labor shows the highest positive impact, as predicted. Medical capital, in contrast, shows a negative impact. Medical capital expense reflects investment in department improvements, primarily on inpatient wards, either acute care or intensive care. Reimbursement changes affected hospitals' incentives, resulting in continually decreasing lengths of stay after 1983. However, adjusted patient days did not decrease over the time period because outpatient admissions tended to increase, partially through a substitution of outpatient services for inpatient services (Menke 1990). Thus, any increases in capital expense in inpatient departments would be associated with decreasing adjusted patient days. The negative coefficient on medical capital probably reflects this trend. The negative value for the time coefficient indicates a shift of production set to lower output levels in the recent years.

Table 4 is of more practical interest since it shows the dependence of revenues on unit change in input costs. The results indicate that revenues increase by a factor of 2.9 for every unit increase in IT labor. A similarly large revenue contribution of medical labor is found. Labor is typically scheduled to meet demand, and therefore uses fewer units than capital to achieve revenue growth. This pattern is consistent with hospital reimbursement schemes that were primarily cost-plus until the mid 1980s. Medical IT capital also shows

a high marginal revenue contribution for the sample. This is not surprising given that acquisition of medical IT capital equipment by hospitals was restricted by legislation and the prices of typical services using this equipment were high, thereby affecting revenues. Although IT capital exhibits a positive productivity impact, it does not affect revenues as much as labor does. Consistent with prior healthcare studies (Zucherman et al. 1994), the teaching status variable reflects a negative influence on production of services (Table 3). The lower productivity of teaching hospitals suggests overutilization of labor and capital. Several physicians and paid interns are assigned to one patient, and cases tend to be highly complex, resulting in lower productivity. Our model myopically considers only one objective (cost minimization) and one output (revenues). Hence, we are not able to capture teaching hospitals' multiple objectives, which include not only providing healthcare services but also developing healthcare professionals. However, this study does validate extant hypotheses that organizational variables such as teaching status do affect hospitals overall, and lack of a control for teaching status may result in potential underestimation of parameters. Similarly, in various industries in which IT productivity is being determined, different organizational variables may lead to the overestimation or underestimation of productivity contribution.

Conclusions

This study uses a healthcare setting to examine the productivity of IT. Since hospitals are regulated, detailed data (e.g., salaries, direct costs, depreciation) are available at the department level. These data allow more

Table 3 Parameter Estimates from Stochastic Production Frontier

Parameter	Estimate	t-Statistic
Constant	5.2901	133.11
Non-IT Labor	0.8626	143.51
IT labor	0.1804	118.89
Medical Capital	-0.0845	-36.68
Medical IT Capital	0.0608	49.15
IT Capital	0.0179	36.21
Teaching Control	-0.1200	-6.71
Time control	-0.0273	-24.09
σ_u	0.1626	20.80
σ_v	0.1133	41.43

For all values, $p < 0.0005$.

Note. Adjusted patient days is the output measure.

Table 4 Mean Marginal Revenue Contribution of Input Factors Using Stochastic Frontier Formulation

Factor	Mean Marginal Revenue Contribution	Std. Deviation
IT Capital	0.633	0.417
Medical Capital	-0.395	0.233
Medical IT Capital	1.145	0.544
IT Labor	2.961	0.762
Medical Labor	2.278	0.401

refined model specification and reduce the level of measurement error in output and input variables. A stochastic frontier approach is used that assumes inefficiency of processes. This approach models the production process for each hospital more realistically. Capital expense is categorized into three separate categories: IT capital, medical IT capital, and medical capital. Control variables for teaching hospitals and for time-related factors are included in the model, and our sample period is relatively long (1976–1994).

Results obtained with these methodological refinements show that both IT and medical IT capital exhibit a positive influence on output. A positive mean marginal revenue contribution is also obtained for IT and medical IT capital investments. In addition, our results indicate that IT labor and medical labor exhibit a positive influence on output as well as a positive impact on mean marginal revenue. However, we find that medical capital appears to be negatively associated with output during this time period. This finding may reflect hospitals' attempts to contain costs by substituting outpatient services for inpatient services, resulting in a decrease in length of stay for acute care wards (where medical capital is invested) and increasing outpatient visits for diagnostic tests and procedures (where medical IT capital is invested). Marginal revenue contribution of the inputs (in increasing order) are medical capital, IT capital, medical IT capital, medical labor, and IT labor. Medical IT capital contributed nearly 100 percent more than IT capital, while labor components contributed over 200 percent more than IT capital. Finally, consistent with prior research, we find that teaching hospitals perform poorly relative to the rest of the sample.

Similar to prior research that aggregates across various types of capital, this study is subject to problems that occur when the productivity impacts of different information technologies are averaged. When information technology is aggregated over mainframes, personal computers, and networks, the productivity impact of IT may be understated, since mainframes are frequently used past their accounting depreciation life and since the prices of PCs dropped over the period in question. Hospitals were slow in adopting new IT and most IT managers kept tight control over the mainframe installations, so IT capital was probably not re-

placed in a timely manner. While the lower prices of a unit of new IT and extended use of old IT may have somewhat balanced each other, the exact effects of these influences are difficult to gauge at this level of analysis.

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Appendix

A. Calculation of Capital Stock. Let K_{t-1976} be the capital stock for the asset in year t , d_{t-1976} be the depreciation rate of capital stock, and D_{t-1976} be the depreciated capital stock. $t = -1$ represents the year 1975 and $t = 0$ represents 1976. We assume that $K_{-1} = K_0/d_{-1}$, then $\tilde{D}_0 = (K_{-1} - K_{-1}d_{-1})d_0$.

If $D_0 \geq \tilde{D}_0$ then $I_0 = D_0 - \tilde{D}_0/d_0$, else $I_0 = 0$. So that $K_0 = (K_{-1} - K_{-1}d_{-1}) + I_0$.

The algorithm can be applied recursively to all future years to determine capital stock in each year. Thus, for any year t in the future, $\tilde{D}_{t-1976} = (K_{t-1977} - K_{t-1977}d_{t-1977})d_{t-1976}$.

If $D_{t-1976} \geq \tilde{D}_{t-1976}$ then $I_{t-1976} = D_{t-1976} - \tilde{D}_{t-1976}/d_{t-1976}$ else $I_{t-1976} = 0$. $K_{t-1976} = (K_{t-1977} - K_{t-1977}d_{t-1977}) + I_{t-1976}$.

B. Likelihood Function. Adapting from Schmidt and Lovell (1979), we derived the log likelihood expression from Equation (11) as

$$\begin{aligned} & -\ln(\sqrt{\sigma_v^2 + \sigma_u^2}) - \frac{1}{2} \ln(|\tilde{\Sigma}|) + \ln\left(\sum_i (a_i)\right) - \frac{1}{2} \tilde{\varepsilon} \tilde{\Sigma}^{-1} \tilde{\varepsilon} \\ & - \frac{\ln y - \sum_i (a_i \ln z_i) - b * t - c * D}{\sqrt{\sigma_v^2 + \sigma_u^2}} \\ & + \ln\left(1 - F\left(\frac{\left(\ln y - \sum_i (a_i \ln z_i) - b * t - c * D\right) \times \frac{\sigma_u}{\sigma_v}}{\sqrt{\sigma_v^2 + \sigma_u^2}}\right)\right) \end{aligned} \quad (12)$$

where σ_u and σ_v are the standard deviations of u and v , respectively, that also are parameters to be estimated, $\tilde{\varepsilon}$ is a 4×1 vector of error terms from Equation (11), and $\tilde{\Sigma}$ is a 4×4 covariance matrix derived from $(\tilde{\varepsilon} - \bar{\mu})(\tilde{\varepsilon} - \bar{\mu})^T$ where $\bar{\mu}$ is the average of $\tilde{\varepsilon}$ and T stands for the transpose of a matrix. $|\tilde{\Sigma}|$ is the determinant of the matrix.

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