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Abstract

This paper explores the impact of information technology (IT) on organizational productivity in the healthcare industry using a regression splines (RS) based approach that offers the opportunity for rich analysis. Application of the RS based approach offered additional valuable insights that should contribute to our understanding the complex relationship between investments in IT and organizational productivity. For example, the results of this study suggest that investments in the IT Stock has a positive statistically significant impact on productivity only under certain conditions, and that this impact of IT is not uniform but is conditioned both by the amounts invested in the IT Stock and Non-IT Capital.

Keywords: Information technology investments, productivity, regression splines, data mining, MARS

Introduction

Investments in information technology (IT) have grown continuously over the past thirty years (Dewan and Min 1997), with IT becoming the largest item of capital expenditure in most organizations (Farbey et al. 1999). While organizations have invested in IT as a means to improve organizational performance, some previous studies have failed to show any evidence of IT impact on organizational productivity. Thus the issue of the "IT productivity paradox" has been debated by IS researchers since the mid-1980s (Brynjolfsson 1993; Brynjolfsson and Hitt 1996; Hitt and Brynjolfsson 1996; Prasad and Harker 1997; Sircar et al. 2000). However, recent firm level studies have claimed that IT productivity paradox no longer exists (e.g. Garretson 1999; Hitt and Brynjolfsson 1996; Shao and Lin 2000 and 2001).

In this paper, we explore the IT impact on productivity of Healthcare industry. We utilize a dataset that was also used in other studies (Menon et al. 2000, Lee and Menon 2000), but apply a relatively new technique, multivariate adaptive regression splines (MARS) that, we believe, offers the opportunity for rich analysis.

Overview on Previous Research

Several studies have examined the IT impact on productivity at the firm level but their findings have been inconsistent. While Loveman (1994) found no evidence of productivity increase from IT investment, some studies have mixed results. Weil (1992) found that transactional IT investments had a positive impact on firm performance but strategic IT or informational IT did not. Prasad and Harker (1997) found that IT labor produced substantial high returns in productivity but IT capital did not. Lee and Menon (2000) found that IT capital has associated with increased productivity but IT labor did not.

On the other hand, some studies have found a positive relationship. Hitt and Brynjolfsson (1996) found that IT spending has a positive impact on productivity and provided significant value for consumers. Shao and Lin (2001) found that IT has a positive effect on technical efficiency in the production process whether IT investments are treated as a firm-specific factor or a production factor. Menon et al. (2000) found that non-IT labor showed the highest positive impact on productivity, IT labor and non-IT capital contributed positively to productivity, IT capital contributed low average productivity but non-IT capital showed a negative impact on productivity. Overall, findings from the research are thus inconclusive. Table 1 included the summary of the previous studies of IT impacts on organizational productivity.

Table 1. Summary of Empirical Firm Level Studies of the IT Productivity

Study	Sample Size/ period	Findings
Weil (1992)	33 / 1982-1987	Transactional IT: ↑ Strategic or informational IT: ↔
Loveman (1994)	60 / 1978-1984	Productivity: ↔
Hitt & Brynjolfsson (1996)	1109 / 1988-1992	Productivity and consumer value: ↑
Prasad & Harker (1997)	47/ 1993-1995	IT labor and productivity: ↑ IT capital and productivity: ↔ or
Shao & Lin (2001)	1115/ 1988-1992	IT and technical efficiency: ↑ thus, IT and productivity: ↑
Lee & Menon (2000)	1064/ 1976 - 1994	IT capital and Productivity: ↑ IT labor and Productivity:
Menon et al. (2000)	1064 / 1976 -1994	Between medical labor, IT labor, medical IT capital and productivity: ↑ Medical capital and productivity: ↓

Legend:
- ↑ positive relationship
- ↔ No effect
- ↓ negative relationship

Description of the Dataset

We used a dataset that has also been previously used in other studies on IT and productivity (Menon et al. 2000; Lee and Menon 2000). The Washington State Department of Health (DOH) collected financial data of each hospital in the Washington state. The dataset includes the departmental-level costs and charges for 83 accounts for each hospital for the period from 1975 to 1994. Each hospital accumulates its charges and costs based on the account number. Overall, the data consists of 1130 observations. The dataset excludes any specialized hospitals such as psychiatric and substance abuse treatment centers. Charges include the total dollars billed for patient services during the period, not considering any reimbursement. Costs include expenses such as salaries and wages, employee benefits, supplies, and rental/lease. Capital expenses were categorized as IT Capital, Medical IT Capital, and Non-IT Capital based on departmental account as shown in Table 2. Any capital expense in remaining accounts is considered as Non-IT Capital. The salaries and employee benefits incurred in departments where their capital expenses were classified as IT Capital were categorized as IT Labor and these expenses incurred in remaining departments were classified as Non-IT Labor. From these variables, IT Stock, which represents IT investments, is constructed by combining IT Capital and a capitalized value of IT Labor expenses. Medical IT Capital is considered as part of IT Capital and IT Labor is treated as part of IT investments since IT Labor represents a type of expenditure that produce a capital asset which lasts three years on the average (e.g. Hitt and Brynjolfsson 1996).

Thus, the data are classified as three different categories, such as IT Stock, Non-IT Capital, and non-IT Labor. The output is the hospital performance measure, 'Adjusted Patient Days', which can be calculated as the sum of inpatient days and outpatient days. For detailed description of variables, refer to the study by Menon et al. (2000).

Table 2. Variable Definitions (Source: Menon, Lee, and Eldenburg, 2000 & Menon's SAS program)

Variable	Description (or Departmental Account)
Adjusted patient days (Q)	Adjusted patient days (sum of inpatient days and outpatient days). Deflated by the output price (see below).
IT Stock (T)	Calculated as IT Capital plus Medical IT Capital plus three times IT Labor
IT Capital	Data Processing, Communications, Admitting, Patient Accounts, Central Services, Purchasing, Accounting, Medical Records, Personnel, Medical Library, Medical Staff, and Utilization Management. Deflated by Price Deflator for Fixed Investment for IT from WEFA-1994
Medical IT Capital	MRI, CT Scanning Services, Surgical Services, Recovery Room, Anesthesiology, IV Therapy Services, Electrodiagnosis, Radiology-Diagnostic, Radiology-Therapeutic, Emergency Room, Nuclear Medicine, Electromyography, Lithotripsy, Organ Acquisitions, Outpatient Chemical Deposit. Deflated by Price Deflator for Fixed Investment for IT from WEFA-1994
Non-IT Capital (K)	Intensive/Coronary Care, Semi-Intensive Care, Acute Care, Physical Rehabilitation, Psychiatric, Nursery, Laboratory, Pharmacy, Home Care Services. Deflated by Price Deflator for Fixed Investment for Non-IT from WEFA –1994.
IT Labor	Salaries and employee benefits charged to IT Capital accounts. Deflated by Labor Price (see below).
Medical Labor (L)	Salaries, employee benefits, and physicians' salaries charged to accounts other than IT Capital accounts. Deflated by Labor Price (see below).
Labor Price	Employment Price Index for health care services from Bureau of Labor Statistics (BLS) (1995)
Output Price	Consumer Price Index for health care services from WEFA (1994)

The Production Function

The theory of production assumes that a firm uses various inputs to produce its outputs based on the rules specified by firm's production function (Henderson and Quandt 1980). Many previous studies that have explored the relationship between IT investments and productivity have also used this theoretical base (e.g. Loveman 1994; Hitt and Brynjolfsson 1996; Dewan & Min 1997; Shao 2000). For this study the output (Q) is the hospital's *Adjusted Patient Days* (see Table 2) and the input variables are *Non-IT Capital* (K), *Non-IT Labor* (L), and *IT Stock* (T*)*, where IT Stock includes both IT Capital and IT Labor in a manner similar to its use in the study by Hitt and Brynjolfsson (1996). Since we assuming that an hospital's *Adjusted Patient Days* (Q) depends on the use of *IT Stock (T)*, *Non-IT Capital (K)*, and the *Non-IT Labor (L)*, then our production function has the following form:

$$Q = f\,(K, L, T) \tag{1}$$

Although the most widely known production function is the Cobb-Douglas function, the translog production function has also been used. While other studies have used it to explain the impact of IT investments on productivity, those studies have used regression analysis to identify statistically significant variables and interactions. In this study, our analysis is also based on translog production function because it enables us to explore interactions between our input variables. However, unlike other studies, we use regression splines (RS) analysis to understand the complex relationship between IT investments and productivity in the healthcare sector.

The Translog function is a generalization of the Cobb-Douglas functional form, relaxing the constraints of the substitution assumptions and allows no restriction on returns to scale. Thus, the Translog production function is more flexible functional form although it presents more parameters than the Cobb-Douglas (Evans et al. 2000). In addition, it allows the testing interactions among various inputs. In general, the Translog function has the following form:

$$\log_e Q = \log_e \gamma_0 + \sum_i \alpha_i \log_e v_i + ½ \sum_i \sum_j \beta_{ij} \log_e v_j \log_e v_i \tag{2}$$

where v_i .. v_n are the firm's inputs; and $\beta_{ij} = \beta_{ji}$ for all i, j.

The relevant Translog function that applies to our production function Q = f(K, L,T) can be expressed as:

$$\log_e Q = \beta_0 + \beta_K \log_e K + \beta_L \log_e L + \beta_T \log_e T + 1/2\, \beta_{KK} (\log_e K)^2 + 1/2 \beta_{LL} (\log_e L)^2 + 1/2\, \beta_{TT} (\log_e T)^2 + \beta_{KL} \log_e K \log_e L + \beta_{LT} \log_e L \log_e T + \beta_{TK} \log_e T \log_e K \quad (3)$$

Overview on Regression Splines

Regression equations attempt to model the relationship between outcome and predictor variables using a single function (e.g. linear, log linear) of the predictor variables, describing the contribution of each predictor (independent) variable with a single coefficient. To capture any relevant non-linearity, higher order terms (x^2, x^3, etc.) may be introduced but the coefficients of these terms will be estimated using the data globally and thus, local features of the true function might not be captured (Hastie and Tibshirani 1990).

On the other hand, a Regression Spline (RS) approach models the mean outcome as piecewise polynomial, such as piecewise continuous linear functions (linear splines) or piecewise cubic functions with continuous derivative of predictor variable (Hastie and Tibshirani 1990). A piecewise polynomial function $f(x)$ can be obtained by dividing the range of each predictor variable into one or more intervals and representing function f by a separate polynomial in each interval (Hastie et al. 2001). Thus, splines are described as piecewise polynomials whose segments have been joined together smoothly at the knots (Eubank 1988), where a *knot* specifies the end of one region of data and the beginning of another (Steinberg et al. 1999). A regression spline function can be expressed as a linear combination of piecewise polynomial *basis functions (BF)* that are joined together smoothly at the knots and the coefficients of the basis function are estimated by minimizing the sum of square errors. Since this process is same as the estimation process of regression, this estimated spline is called the Regression Spline. Because segmented nature of piecewise polynomials adjusts more effectively to local characteristics of a function or data, they provide more flexibility than polynomials. RS performs a polynomial fit in each region with constraints at the knots using the least squares criterion. Accordingly, *the parameters of the regression functions change from one region to another*.

Multivariate Adaptive Regression Splines (MARS) approach was motivated by adaptive regression spline (Hastie and Tibshirani 1990) and the recursive partitioning regression (RPR) approach (Breiman et al. 1984). Although RPR is commonly used for multivariate function approximation, it is discontinuous at the region boundaries. In the RPR, the estimated mean function f (x_1, …x_q), can be written as a linear combination of product of step function, i.e.

$$f(x_1,\ldots x_q) = \sum_{k=1}^{K} \beta \Pi f_{ij}(x_i)$$

where K is the number of final nodes, $f_{ij}(x_i) = 0$ if $x_i < b_{ij}$, 1 if $x_i >= b_{ij}$, and β_k and b_{ij} are parameters to be determined.

MARS improved this disadvantage of RPR while it retained the adaptability of RPR (Friedman 1991). MARS is highly adaptive and automatically selects locations and degree of knots. It builds a model in a two-phase process, using a forward stepwise regression selection and backwards-stepwise deletion strategy. In the first phase, MARS builds an overfitted model by adding basis functions. In the second phase, basis functions that have the least contribution to the model are deleted and the model is optimized (Steinberg et al. 1999). Therefore, the function obtained using the MARS approach can be described as the form:

$$Y = \beta_0 + \sum_{k=1}^{K} \beta_k h_k(x)$$

where β_0 is the coefficient of the constant basis function, $\beta_k (i = 1, \ldots, K)$ are the coefficients of the basis functions, K is the number of basis functions in the model, h_k(x) are product of spline basis functions, i.e., $h_k(x) = h_k(x_1, \ldots x_q) = \Pi_{ij} f_{ij}(x_i)$ where $f_{ij}(x)$ is spline basis function. MARS uses the basis functions in pairs of the form $(x - t)_+$ and $(t - x)_+$ where t is the knot. The "+" represents positive part, thus, $(x - t)_+$ means $x - t$ if $x > t$ or 0 if otherwise and $(t - x)_+$ means $t - x$ if $x < t$ or 0 if otherwise (Hastie and Tibshirani 1990; Hastie et al. 2001). MARS provides ANOVA decomposition, which identifies the relative contributions of each of the predictor variables and the interactions between variables, and handles missing values (Friedman 1991).

A MARS model can be generated that allows no interaction between the input variables, or to permit interactions between variables of any order. MARS models that involve interactions between variables have a hierarchical, tree-like structure, with parent and child relationships between basis functions. Modeling the translog function using MARS involves permitting two-way interactions between variables. Thus similar to standard regression analysis, MARS can be used to identify interactions between variables in the production process, but in addition MARS can be used to identify the hierarchical nature of the interaction.

Empirical Results and Discussion

Description of the Results

The RS model that was generated had a R-Squared value of 0.90, which suggests that it has relatively high predictive power. Table 3 describes data that includes the mean log value, standard deviation, and the sample size and Table 4 suggests the order of importance of variables in this predictive model. Table 5 describes the RS model in terms of basis functions and their coefficients.

Table 3. Sample Statistics

Variable	Mean	SD	N
$\log_e Q$	10.514	0.850	1130
$\log_e T$	15.526	0.904	1130
$\log_e K$	13.266	1.266	1130
$\log_e L$	16.136	0.965	1130

Table 4. Relative Importance of Variables

Variable	Cost of Omission	Importance
$\log_e K$	0.143	100.000
$\log_e L$	0.139	97.271
$\log_e T$	0.081	30.360

Table 5. Final Model from the MARS

	Basis Function (BF)	Coefficient	Variable	Parent	Knot (log value)
0		11.923			
1	BF1 = max (0, $\log_e L$ – 16.703);	1.114	$\log_e L$		16.703
2	BF2 = max (0, 16.703 – $\log_e L$);	-1.243	$\log_e L$		16.703
3	BF3 = max (0, $\log_e K$ – 12.220);	-0.589	$\log_e K$		12.220
4	BF4 = max (0, 12.220 – $\log_e K$)				
5	BF5 = max (0, $\log_e L$ – 15.350) * BF4;	-1.067	$\log_e L$	$\log_e K$	15.350
6	BF6 = max (0, 15.350 – $\log_e L$) * BF4;	0.370	$\log_e L$	$\log_e K$	15.350
7	BF7 = max (0, $\log_e T$ –14.086) * BF4;	0.611	$\log_e T$	$\log_e K$	14.086
10	BF10 = max (0, 15.967 - $\log_e T$);	-0.207	$\log_e T$		15.967
11	BF11 = max (0, $\log_e T$ – 14.738) * BF3;	0.050	$\log_e T$	$\log_e K$	14.738
12	BF12 = max (0, 14.738 - $\log_e T$) * BF3;	0.856	$\log_e T$	$\log_e K$	14.738
13	BF13 = max (0, $\log_e K$ – 13.714) * BF2;	0.597	$\log_e K$	$\log_e L$	13.714

From these basis functions, we can identify the knots for our input variables:

- non-IT Labor (L): L_{cv1} and L_{cv2}, where $\log_e(L_{cv1}) = 16.703$ and $\log_e(L_{cv2}) = 15.350$
- IT Stock (T): T_{cv1}, T_{cv2}, and T_{cv3} where $\log_e(T_{cv1}) = 14.086$, $\log_e(T_{cv2}) = 15.967$, and $\log_e(T_{cv3}) = 14.738$.
- Non-IT Capital (K): K_{cv1} and K_{cv2} where $\log_e(K_{cv1}) = 12.220$ and $\log_e(K_{cv2}) = 13.714$.

Given these basis functions and their coefficients described in Table 5, our translog function can be expressed as follows:

$$Q = 11.923 + 1.114{*}BF1 - 1.243{*}BF2 - 0.589{*}BF3 - 1.067{*}BF5 + 0.370{*}BF6 + 0.611{*}BF7 - 0.207{*}BF10 + 0.050{*}BF11 + 0.856{*}BF12 + 0.597{*}BF13$$

The reader should note that if the sign of the coefficient of a basis function is the same as the sign of the variable in that function (e.g. BF1, BF10) then the contribution of given variable in terms of that basis function is positive, while if the corresponding signs are different then the contribution of given variable in terms of that basis function is negative (e.g. BF3, BF12).

Interpretation of the Results

These results suggest the following:

(1) Investments in IT Stock ($\log_e T$)
- They have statistically significant impact on productivity since IT Stock involved in four (4) of the basis functions (i.e. BF7, BF10, BF11, and BF12) that are in the RS model.
- The overall impact on organizational productivity is conditioned both by the amount invested in the IT Stock (see BF10) and the investments in Non-IT Capital (see BF7, BF11, and BF12).
- The impact of investments in the IT Stock (T) is not conditioned by investments of Non-IT Labor (L) as none of the basis functions that involve the IT Stock (i.e. BF7, BF10, BF11, and BF12) has Non-IT Labor (L) as a parent.
- The overall impact on organizational productivity is not uniform. There are different coefficients for each of the basis functions that involve the IT Stock (i.e. BF7, BF10, BF11, and BF12).
- Under certain conditions, investments in IT Stock have a positive statistically significant impact on productivity. For example if $\log_e K < \log_e K_{cv1}$ (see BF4), then the impact of IT investments on productivity is positive as for each of the relevant basis functions (BF) that involve IT Stock, the sign of the variable in the BF and the sign of the coefficient of the BF are the same (i.e. BF10, BF7).
- Under certain conditions, investments in IT Stock could have a negative statistically significant impact on productivity. For example, if $\log_e K > \log_e K_{cv1}$ (see BF3), and $\log_e T < \log_e T_{cv3}$) (see BF12), the overall impact of $\log_e T$ could be negative. In this case, although the contribution of the IT Stock from BF10 is positive, its contribution from BF12 is negative (since the sign of $\log_e T$ in BF12 is negative while the sign of the coefficient of the BF12 is positive), and so the overall impact could be negative.

(2) Investments in Non-IT Labor ($\log_e L$)
- They have statistically significant impact on productivity since Non-IT Labor involved in four (4) of the basis functions (e.g., BF1, BF2, BF5, and BF6) that are in the RS model.
- The overall impact of investments is determined both by the amount invested in the Non-IT Labor (see BF1 and BF2) and the investments in Non-IT Capital (see BF5 and BF6).
- The overall impact of investments on organizational productivity is not uniform. There are different coefficients for each of the basis functions that involve the Non-IT Labor (i.e. BF1, BF2, BF5, and BF6).

(2) Investments in the Non-IT Capital ($\log_e K$)
- They have statistically significant impact on productivity through interactions with other variables (IT Stock (T) or Non-IT Labor (L)) since Non-IT Capital involved in seven (7) of the basis functions (two as a main variable –BF3 and BF13, five as a parent of the interactions – BF5, BF6, BF7, BF11, and BF12).
- In terms of their impact on productivity, the interaction between Non-IT Capital (K) and Non-IT Labor (L) is a complex one, as both variables condition each other (i.e. BF5, BF6, and BF13).

Conclusion and Discussion

As investments in IT have continuously increased, numerous studies have attempted to estimate the impact of IT investments but the findings of previous studies are inconclusive. In this study, we introduce regression splines approach to explore the impact of IT on productivity in the Healthcare industry. We believe that our new technique offers additional valuable insights in understanding the IT impact. We found that IT Stock has a positive statistically significant impact on productivity only under certain conditions. Also, the impact of IT is not uniform and it is conditioned both by the amounts invested in the IT Stock and Non-IT Capital. Our study indicates that Non-IT Labor has a positive impact on productivity but again its impact is conditioned by the amounts invested in the Non-IT Labor and Non-IT Capital.

Our findings could be beneficial to managers in making IT investments decisions. For example, our results suggest that managers should not consider the amount of investment in IT separately but together with other investments, such as Non-IT Labor and Non-IT Capital, which have been previously invested in order to identify the optimum level of IT investment for increasing organizational productivity.

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