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The productivity impact of information technology in the healthcare industry: an empirical study using a regression spline-based approach

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Abstract

This paper explores the productivity impact of information technology (IT) in the healthcare industry using a regression spline (RS)-based approach. Application of the RS-based approach offered additional valuable insights that contribute to our understanding of 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 impact on productivity only under certain conditions, and that this impact of IT is not uniform but is conditioned both by the amount invested in the IT Stock and the investments in Non-IT Capital.

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1. Introduction

Investments in information technology (IT) have grown continuously over the past 30 years [1]. Recently, IT became the largest item of capital expenditure in most organizations [2]. While organizations have invested in IT as a means to improve organizational performance, many previous IS researchers have failed to show any evidence of the IT impact on organizational productivity. This ‘IT productivity paradox’ has been a debated issue since the mid-1980s [3–7]. While recent firm level studies have claimed that the IT productivity paradox no longer exists [5, 8–10], Morgan Stanley reported that US companies wasted \$130 billion in the past 2 years on technology [11].

In this paper, we explore the productivity impact of IT investments in the healthcare industry utilizing a dataset that has been used in another study [12]. In this study, we take another look at this issue by applying a relatively new technique, multivariate adaptive regression splines (MARS) that, we believe, offers the opportunity for rich analysis.

2. Overview on previous research

Several studies have examined the productivity impact of IT investments, and their findings have been inconsistent. While Loveman [13] found no evidence of productivity increase from IT investments, some studies have mixed results. Weill [14] found that transactional IT investments had a positive impact on firm performance but strategic IT or informational IT did not. Prasad and Harker [6] found that IT labor produced substantial high returns in productivity but IT capital did not. Lee and Menon [15] found that IT capital was associated with increased productivity but IT labor did not. On the other hand, some studies have found a positive relationship. Hitt and Brynjolfsson [5] found that IT spending has a positive impact on productivity and provided significant value for consumers. Shao and Lin [10] 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. [12] found that non-IT labor showed the highest positive impact on productivity. In their study, IT labor and non-IT labor contributed positively to productivity while IT capital contributed low average productivity. However, non-IT capital showed a negative

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Table 1
Summary of empirical firm level studies of the IT productivity

Study	Sample size/period	Findings
Ref. [14]	33/1982–1987	Transactional IT: ↑; strategic or informational IT: ↔
Ref. [13]	60/1978–1984	Productivity: ↔
Ref. [5]	1109/1988–1992	Productivity and consumer value: ↑
Ref. [6]	47/1993–1995	IT labor and productivity: ↑; IT capital and productivity: ↔ or: ↓
Ref. [10]	1115/1988–1992	IT and technical efficiency: ↑; thus, IT and productivity: ↑
Ref. [15]	1064/1976–1994	IT capital and productivity: ↑; IT labor and productivity: ↓
Ref. [12]	1064/1976–1994	Between medical labor, IT labor, medical IT capital and productivity: ↑; medical capital and productivity: ↓

↑ : Positive relationship (or increase productivity); ↔ : no effect; ↓ : negative relationship (or decrease productivity).

impact on productivity in their study. Table 1 includes a summary of the previous IT productivity research.

3. Description of the dataset

We used a dataset that has also been previously used in another study on the impact of IT investments on productivity in the healthcare industry [12]. The source data were collected by the Washington State Department of Health (DOH), and include the departmental-level costs and charges for 83 accounts for each hospital in the Washington state for the period from 1976 to 1994. The dataset excludes any specialized hospitals such as psychiatric and substance abuse treatment centers. Overall, the dataset consists of 1130¹ observations.

Each hospital accumulates its charges and costs based on the account number. 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*. IT Capital includes capital expenses incurred mainly for administrative purposes in the departmental accounts that are shown in Table 2. Medical IT Capital includes capital expenses incurred for the equipment used for diagnosing and therapeutics in the departmental accounts that are shown in Table 2. Non-IT Capital includes capital expenses incurred for the equipment used only for therapeutic purposes and also includes any capital expenses in remaining departmental accounts. Labor expenses were classified as two categories: *IT Labor* and *Non-IT Labor*. The salaries and employee benefits incurred in departments where their capital expenses were classified as IT Capital were categorized as IT Labor and those 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 investments

and IT Labor is treated as part of IT investments since IT Labor represents a type of expenditure that produces a capital asset which lasts 3 years on the average [5]. Thus, the data are categorized into three variables: 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, the reader may refer to the study by Menon et al. [12].

4. The production function

The theory of production assumes that a firm uses various inputs to produce its outputs based on the rules specified by the firm's production function [16]. Many previous studies that have explored the relationship between IT investments and productivity have also used this theoretical base [1,5,13,17]. For this study, the target (i.e. dependent) variable, Q is the hospital's Adjusted Patient Days (see Table 2) and the predictor (i.e. independent) variables are Non-IT Capital (K), Non-IT Labor (L), and IT Stock (T), where IT Stock includes IT Capital, Medical IT Capital and IT Labor in a manner similar to its use in the study by Hitt and Brynjolfsson [5]. Since we assume that a 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:

$$Q = f(K, L, T) \quad (1)$$

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 predictor (or independent) variables. However, unlike other studies, we use regression splines (RS) analysis to understand the complex relationship between IT investments and productivity in the healthcare industry.

¹ The number of observations is larger than that in Ref. [12] because MARS handles missing values differently compared to regression model.

Table 2
Variable definitions (source: Ref. [12] and Menon's SAS program)

Variable	Description (or departmental account)
Adjusted Patient Days (Q)	Adjusted patient days (sum of inpatient days and outpatient days). Outpatient days are derived by dividing outpatient revenue by inpatient revenue per day. 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 (T)	Capital expenses incurred in 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	Capital expenses incurred in 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)	Capital expenses incurred in intensive/coronary care, semi-intensive care, acute care, physical rehabilitation, psychiatric, nursery, laboratory, pharmacy, home care services and any remaining accounts. 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)
Non-IT 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 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 a more flexible functional form although it presents more parameters than the Cobb-Douglas [18]. In addition, it allows for testing of interactions among various inputs. In general, the Translog function has the following form:

$$\log_e Q = \log_e \gamma_0 + \sum_i \alpha_i \log_e v_i + 1/2 \sum_i \sum_j \beta_{ij} \log_e v_j \log_e v_i \quad (2)$$

where $v_1 \dots v_n$ 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:

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

5. Overview on Regression Splines

Regression equations attempt to model the relationship between target 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. If the relationship is linear or approximately linear, the regression equation can provide an accurate and useful estimate. 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 over the range of the whole dataset (global nature of fit). However, this might not be the most appropriate functional form since it is based on a rigid assumption about the relationship [19]. Thus, if the functional form of the dataset varies with each sub-region, local (i.e. sub-region) features of the true function might not be captured using the regression approach.

On the other hand, an RS approach models the relationship between target and predictor variables using a piecewise polynomial function, such as piecewise continuous linear functions (linear splines) or piecewise cubic functions with continuous derivative of predictor variable [19]. 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 [20]. Thus, splines are described as piecewise polynomials whose segments have been joined together smoothly at the knots [21], where a *knot* specifies the end of one region of data and the beginning of another [22]. An RS 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. 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. Since this process is same as the estimation process of regression, this estimated spline is called the Regression Spline.

MARS approach was motivated by adaptive RS [19] and the recursive partitioning regression (RPR) approach [23]. Although RPR is commonly used for multivariate function approximation, it is discontinuous at the region

boundaries. Thus, MARS improved this disadvantage of RPR while it retained the adaptability of RPR [24]. 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 where removal causes the smallest increase in residual squared error and the model is optimized [20,22]. Therefore, the function obtained using the MARS approach can be described as the form:

$$Y = \beta_0 + \sum_{k=1}^K \beta_k h_k(\mathbf{x}) \quad (4)$$

where β_0 is the coefficient of the constant basis function, β_k ($k = 1, \dots, K$) are the coefficients of the basis functions, K is the number of basis functions in the model, $h_k(\mathbf{x})$ are product of spline basis functions, i.e. $h_k(\mathbf{x}) = h_k(x_1, \dots, x_q) = \prod_{ij} f_{ij}(x_i)$ where $x_1, \dots, x_q$ are the independent variables, f_{ij} is a spline basis function for the i th independent variable x_i at j th knot. 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 [19,20]. MARS provides ANOVA decomposition, which identifies the relative contributions of each of the predictor variables and the interactions between variables, and handles missing values [24].

A MARS model can be generated that allows no interaction between the input variables, or to permit interactions between two or more variables. 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 input variables.

5.1. Comparison to Data Envelopment Analysis

In the past, the Data Envelopment Analysis (DEA) approach has been used in IT productivity research [10]. While both the RS and DEA are considered to be non-parametric approaches to analyzing data, some of the differences between RS and DEA are presented to better understand the characteristics of RS approach.

First, DEA models are used to determine the technical efficiency of each object in the dataset, where the technical efficiency score is a relative value between 0 and 1. Since the technical efficiency of an object in the given dataset could change even if a single observation is added or removed from the dataset, DEA models are typically not used for predictive purposes, but they have

Table 3
Descriptive statistics of the dataset

Name of variable	Variable	Mean	SD	N
Adjusted Patient Days	$\log_e Q$	10.514	0.850	1130
IT Stock	$\log_e T$	15.526	0.904	1130
Non-IT Capital	$\log_e K$	13.266	1.266	1130
Non-IT Labor	$\log_e L$	16.136	0.965	1130

been used in explanatory models in a two-stage process that involves regression as the second stage [10]. However, an RS model can be used for explanation and prediction. Second, using DEA, coefficients (i.e. weights) are generated for both the input production variables (e.g. Non-IT Labor, IT Stock) and the output production variables (e.g. Adjusted Patient Days, Profit), and different observations may have different sets of coefficients. On the other hand, using RS, coefficients are typically generated for the input production variables only.

6. Empirical results and discussion

6.1. 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 descriptive statistics of the dataset, Table 4 describes the relative importance of variables in this model, and Table 5 describes the RS model in terms of basis functions and their coefficients.

As shown in Table 5, the BF8 and BF9 was created but deleted to optimize the model and the BF4 does not have a coefficient since it only exists as part of other basis functions (e.g. BF5, BF6, and BF7). From these basis functions, we can identify the knots for our predictor variables: the knots for IT Stock are represented by T_{cv1} , T_{cv2} , and T_{cv3} where $\log_e(T_{cv1}) = 14.086$, $\log_e(T_{cv2}) = 15.967$, and $\log_e(T_{cv3}) = 14.738$; the knots for Non-IT Labor (L) are represented by L_{cv1} and L_{cv2} , where $\log_e(L_{cv1}) = 16.703$ and $\log_e(L_{cv2}) = 15.350$; and the knots for Non-IT Capital (K) are represented by K_{cv1} and K_{cv2} where $\log_e(K_{cv1}) = 12.220$ and $\log_e(K_{cv2}) = 13.714$.

Table 4
Relative importance of variables

Name of variable	Variable	Cost of omission	Importance
Non-IT Capital	$\log_e K$	0.143	100.000
Non-IT Labor	$\log_e L$	0.139	97.271
IT Stock	$\log_e T$	0.081	30.360

Table 5
Final model

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

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

$$\log_e Q = 11.923 + 1.114*BF1 - 1.243*BF2 - 0.589*$$

$$BF3 - 1.067*BF5 + 0.370*BF6 + 0.611*$$

$$BF7 - 0.207*BF10 + 0.050*BF11 + 0.856*$$

$$BF12 + 0.597*BF13 \quad (5)$$

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).

6.2. Interpretation of the results

These results suggest the following:

(1) Investments in IT Stock (T)

- They have an impact on productivity since IT Stock (T) is 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).
- Under certain conditions, investments in IT Stock (T) could have a negative impact on productivity.

For example, if the investments in Non-IT Capital (K) are greater than K_{cv1} and the investments in IT Stock (T) are less than T_{cv3} , the overall impact of IT Stock could be negative. In this case, although the contribution of the IT Stock from BF10 is positive, its contribution from BF12 is negative because the sign of $\log_e T$ in BF12 is negative while the sign of

the coefficient of the BF12 is positive. Thus, the overall impact could be negative. See Fig. 1.

- Under certain conditions, investments in IT Stock (T) could have a positive impact on productivity.

For example, if the investments in Non-IT Capital (K) are less than K_{cv1} , then the impact of IT Stock (T) on productivity is positive as for each relevant basis functions (BF) that involve IT Stock, the sign of variable in the BF and the sign of the coefficient of the BF are the same (i.e. BF10 and BF 7). See Fig. 2.

- 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

Fig. 1. The impact of investments in IT stock on productivity when Non-IT Capital is fixed at K_{cv1+} . K_{cv1+} means the investments in Non-IT Capital are greater than the value of knot K_{cv1} .

Fig. 2. The impact of investments in IT stock on productivity when Non-IT Capital is fixed at K_{cv1-} . K_{cv1-} means the investments in Non-IT Capital are less than the value of knot K_{cv1} .

Fig. 3. The impact of investments in Non-IT Labor on productivity when Non-IT Capital is fixed at K_{cv1-} .

functions that involve the IT Stock (i.e. BF7, BF10, BF11, and BF12) and the investments in Non-IT Capital (K).

(2) Investments in Non-IT Labor (L)

- They have an impact on productivity since Non-IT Labor (L) 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 the 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). However, the impact of Non-IT Labor (L) investments is always positive whether the investments in Non-IT Capital (K) is less than K_{cv1} (see Fig. 3) or greater than K_{cv1} (see Fig. 4).
- The overall impact of the 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). See Figs. 3 and 4.

(3) Investments in Non-IT Capital (K)

- They have an 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 in 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

Fig. 4. The impact of investments in Non-IT Labor on productivity when Non-IT Capital is fixed at K_{cv1+} .

Fig. 5. The impact of investments in Non-IT Capital on productivity when Non-IT Labor is fixed at L_{cv1-} and IT stock is fixed at T_{cv1-} . Even if IT Stock is fixed at T_{cv1+} , the shape of graph looks very similar.

(i.e. BF5, BF6, and BF13). Also, the overall impact of investments is determined by the amounts invested in the Non-IT Labor, Non-IT Capital, and IT Stock. Findings of our study show that investments in Non-IT Capital (K) have a positive impact on productivity only under certain conditions.

For example, when the investments in Non-IT Labor (L) are less than L_{cv2} , Non-IT Capital (K) has a positive impact if the amount invested in Non-IT Capital is greater than K_{cv1} . In this situation, the amount invested in IT Stock does not change this impact. However, if the amount invested in Non-IT Capital is less than K_{cv1} , it has a negative impact (see Fig. 5).

On the other hand, if the amount invested in Non-IT Labor (L) is greater than L_{cv2} , depending on

Fig. 6. The impact of investments in Non-IT Capital on productivity when Non-IT Labor is fixed at L_{cv2+} and IT stock is fixed at T_{cv1-} .

Fig. 7. The impact of investments in Non-IT Capital on productivity when Non-IT Labor is fixed at L_{cv2+} and IT stock is fixed at T_{cv1+} .

the amount invested in IT Stock (T), the impact of Non-IT Capital (K) changes. In this situation, if the amount invested in IT Stock is less than any of its knots, the impact is positive (see Fig. 6). If the amount invested in IT Stock is greater than T_{cv2} , the impact is negative (see Fig. 7).

7. 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 introduced the RS approach and explored the productivity impact of IT investment in the healthcare industry. We believe that our new technique offered additional valuable insights that contribute to our understanding of complex relationship between investments in IT and organizational productivity.

Our study suggests several facts. First, each input variable has an interaction with other input variables. Thus, considering the investment amount for only one variable may not increase the overall productivity at the firm level. For example, IT Stock in our study has a positive impact on productivity only under certain conditions. When the amount invested in Non-IT Capital is less than one of its knots, K_{cv1} , the impact of IT Stock is positive. Thus, investment decisions in one variable should not be made without considering the amount invested in all other related variables. Second, the impact of IT Stock is not uniform and it is conditioned both by the amount invested in IT Stock and the investments in Non-IT Capital. Thus, identifying an optimum level of the investment in each variable may lead to higher productivity at the firm level. Third, although the overall impact of Non-IT Labor investments is determined both by the amount invested in the Non-IT Labor and the investments in Non-IT Capital, this impact is always positive. Fourth, the overall impact of investments in Non-IT Capital is conditioned by all three categories,

the amounts invested in Non-IT Capital, Non-IT Labor and IT Stock. Thus, its impact on productivity is complex.

Our findings could be valuable for the budgeting process in healthcare organizations, whether this process involves top-down budgeting, bottom-up budgeting, or a hybrid of these approaches. In top-down budgeting, top management develops and approves the enterprise-wide budget even before project and department budgets are developed. Middle and lower level managers then break down these estimates into project and department budgets. The estimates in the enterprise-wide budget are based on the top managers' judgment, experience, and past budget data. With the bottom-up approach, project and department budgets are developed before the enterprise-wide budget, and are combined into the enterprise-wide budget, which is then sent to top-management for approval. In both approaches, top-management has to make enterprise-wide budget decisions based on different scenarios in which investments amounts are aggregated at the organization level and not at the project level. In such situations 'What-If' analysis is often conducted using formal or informal models. The RS model developed in this study offers a formal approach for identifying scenarios under which additional investment in IT could have a positive impact on productivity, and scenarios under which additional investment in IT could have a negative impact on productivity.

8. Limitations of the study and implications for future research

While quantitative analyses based on production function are considered theoretically rigorous [25], this type of analyses cannot explain 'where' and 'how' IT contributes on organizational performance [25,26]. In this paper, we assume that IT investment has a direct impact on organizational performance and treats the relationship between IT investment and organizational performance as a 'black box.' Double dotted line with the arrow at the end in Fig. 8 represents this relationship.

Fig. 8. A conceptual model of the impact of IT investment on organizational productivity—adapted from the models of Weill and Soh and Markus [14,30].

However, recent studies suggested that organizational contextual variables are important factors to consider in determining the impact of IT investment on organizational performance [27–31]. Thus, we would like to incorporate organizational contextual variables such as conversion effectiveness and IT usage that have been identified as important factors in previous studies.

Our study introduces a relatively new technique, MARS, to research on the relationship between IT and productivity. While this technique offers the opportunity for rich analysis, it also introduces concepts (e.g. basis functions, knots) with which the average reader might not be familiar. In this paper, the theoretical model is the translog production function, which limits the number of variables that can be involved in an interaction to two. It should be noted, however, that relationships involving more than two variables can be easily identified using RS analysis. While we could have presented such relationships in this study, the resulting RS model would be more complex and it is likely that the average reader would be unfamiliar with the corresponding theoretical model. We therefore decided that at this stage it would be best to strike a balance by introducing some of the advantages of RS analysis using two-way interaction.

For future research, we also intend to perform another analysis using the same dataset but include only years before Diagnostically Related Group (DRG) or only years after DRG since implementation of DRG in 1983 fundamentally changed how hospitals get reimbursed. Until 1983, hospitals were reimbursed for the service performed on patients. However, after DRGs were implemented, the hospital would be paid the same for patients in the same category. Thus, hospitals were given an incentive to keep costs down by establishing more efficient operations [32]. Since the dataset we used in this study includes the period before and after DRGs, findings from each period could be compared to investigate the difference of the IT impact in the healthcare industry.

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