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Technical efficiency analysis of information technology investments: a two-stage empirical investigation

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Abstract

One of the difficult challenges facing management and researchers today is how to justify costly investments in information technology (IT). This paper presents an approach to investigating the effects of IT on technical efficiency in a firm's production process through a two-stage analytical study with a firm-level data set. In the first stage, a nonparametric frontier method of data envelopment analysis (DEA) is employed to measure technical efficiency scores for the firms. The second stage then utilizes the Tobit model to regress the efficiency scores upon the corresponding IT investments of the firms. Strong statistical evidence is presented to confirm that IT exerts a significant favorable impact on technical efficiency and in turn, gives rise to the productivity growth that was claimed by recent studies of IT economic value. Practical implications are then drawn from the empirical evidence.

Keywords: Information technology; Business value; Technical efficiency; Data envelopment analysis; Tobit regression model; Productivity paradox

1. Introduction

The management of information technology (IT) has become one of the critical issues that managers need to address with great care. The impact of IT has been perceived in almost every part of a business: strategic relevance, process control, research and development, customer service, coordination, costs, etc. At the same time, IT is re-shaping the competition environment in which a business operates and competes. Traditional business rules become obsolete and outdated and are no longer applicable. IT necessitates the establishment of new competition rules that focus more on speed, quality, productivity, efficiency, and customer orientation.

Realizing the ever-increasing importance that IT will carry into the foreseeable future of hyper-competition, businesses are spending more than ever on IT-related expenditures. Enterprise resource planning (ERP) systems, for instance, are purchased to streamline business transactions. TCP/IP networks are laid out to facilitate organizational communication and conduct e-commerce. Advanced databases, assisted by data mining techniques, are installed to analyze the purchasing patterns of customers in the

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hope of expanding into a potential market segment. Over the last decade, IT-related investments in the US have been estimated at a figure as large as US$ 3 trillion [17].

For almost two decades, top management has been wondering if IT spending is worthwhile [48]. The issue of measuring IT returns has become even more pressing because the expenditures on IT equipment and service activities have skyrocketed. Remenyi et al. [45] identified several reasons why management needs to scrutinize IT spending. Firstly, the amounts of financial resources invested in IT are substantial and they are thus very likely to supplant other capital spending. Secondly, IT investments are seldom tied to the revenue-generating or profit-making aspects of the business and as a result, management may not readily agree to IT's value, contribution, or performance. Thirdly, IT investments have frequently been perceived as high risk, compared with other traditional capital budgets.

As a consequence, the issue of how to justify expensive IT investments and substantiate IT's benefits has become important. There are several ways to define and measure IT's business value. The first type of performance measures that managers understand and may prefer are financial, such as revenues, profits, sales growth, return on assets, return on investment, return on equity, and so on (e.g. [7,16,19,20,35,50]). Strassmann, however, contends that this bottom-line type of financial metrics may not serve well as valid performance measures to reflect IT's true benefits. Recent studies on this topic seemed to support this argument [26].

Such a phenomenon prompts researchers to look into the economic aspects of IT impact and turn to performance measures like productivity, capacity utilization, input substitution, relative price, firm boundary, costs, quality, etc. (e.g. [3,6,8,9,18,27,37,41]). These studies of IT economic value are found fragmented and inconclusive at best [40]. For instance, the IT productivity paradox has been a controversial argument of this kind [52]; it casts doubts on the correlation between IT investment and organizational productivity. Not until recently has it been claimed otherwise.

A different line of empirical studies considers the intangible IT benefits that were previously overlooked. These focus on user's perceptions, such as acceptance and satisfaction, and try to capture the effect of various user behavioral and psychological constructs, like participation and attitudes, on the successful outcomes of IT/IS projects [11,30]. These approaches, however, offer no direct links with IT's business value.

Technical efficiency is an important and useful economic measure of organizational performance, which is closely related to, but different from, productivity. Unlike productivity, which has been investigated extensively in the literature of IT business value (e.g. [32,34,38,39,42]), technical efficiency has been studied less frequently by IS researchers. Banker et al. [5] analyzed a chain of fast food restaurants and found that restaurants equipped with a cash register point-of-sale and order-coordination technology tend to be more efficient in their operations than those without the technology.

Our work is carried out in two stages. The first stage involves use of data envelopment analysis (DEA) to construct a nonparametric production frontier and measure the scores of technical efficiency. In the second stage, the efficiency scores are treated as a dependent variable and regressed upon the corresponding IT investments to examine whether IT has a positive influence on technical efficiency. The Tobit regression model [49] is used, instead of the ordinary least squares (OLS), because a significant proportion of the efficiency scores obtained by DEA are equal to 1.

2. Theoretical perspectives and methodologies

2.1. Theory of production

A firm utilizes different kinds of resources (inputs) and produces tangible goods or intangible services (outputs) to satisfy the needs of its customers. The inputs are also termed production factors and usually include capital, labor, materials, etc. The transformation of inputs into outputs is a production process. The production frontier, which characterizes the relationship between inputs and outputs, specifies the maximum output achievable by employing a combination of inputs. The distance between the maximum output (or the production frontier) and the actual output is regarded as its technical inefficiency. Thus, a firm either operates below the frontier when it is technically inefficient, or it operates on the production frontier when it is technically efficient.

Here it is useful to distinguish between technical efficiency and productivity. Technical efficiency is concerned with getting more out of input resources with an extant production technology. In this regard, technical efficiency focuses on either the output side or the input side of a production process. An indicator of technical efficiency can thus be actual output versus expected output (given some input amounts) or resources actually consumed versus resources expected to be consumed (for producing a certain level of output).

Productivity, on the other hand, indicates the effective use of overall resources, without implying any production technology. Productivity evaluates what come out of the production process against what are consumed to produce them. Productivity growth is then measured as a set of successive indices that compared outputs to inputs. A crucial connection between technical efficiency and productivity can be established: productivity growth is a composite index of the change in technical efficiency and the shift in the production frontiers [23,31]. That is,

$$\text{Productivity growth} = \text{technical efficiency change} \times \text{technical change}$$

Therefore, technical efficiency is one component for determining a firm's productivity index.

There are two different approaches to measuring technical efficiency: parametric and nonparametric production frontiers [46]. The parametric approach requires the assumption of a functional form (e.g. Cobb–Douglas, translog, CES, etc.) to be made for the production frontier; it uses the statistical estimation to estimate the coefficients of the production function as well as the technical efficiency [33]. Since the parametric production frontier is assumed to be the "true" frontier, the scores of technical efficiency obtained are regarded as absolute technical efficiency. One potential drawback of the parametric production frontier is the possible misspecification of a functional form for the production process.

Nonparametric production frontiers, on the other hand, are based on mathematical programming and do not make any assumptions about the functional form. The data points in the data set are compared with one another for efficiency. The most efficient observations are utilized to construct the piece-wise linear convex nonparametric frontier. As a result, nonparametric production frontiers are employed to measure relative technical efficiency among the observations.

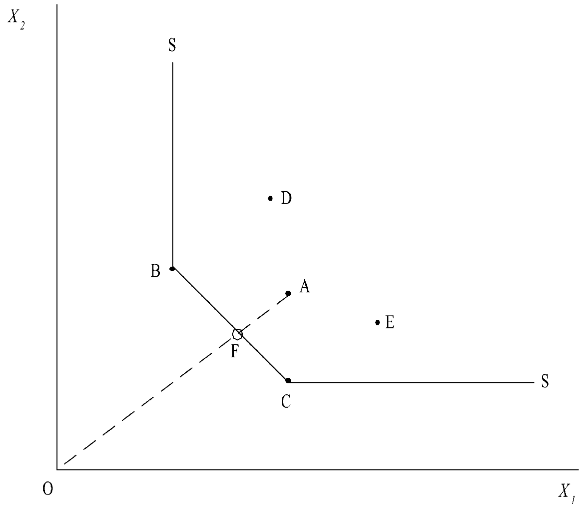

Fig. 1. Piece-wise linear convex isoquant SS and technical efficiency.

Fig. 1 illustrates the concept of a piece-wise linear convex isoquant in a production process, wherein two inputs X_1 and X_2 are used to produce output Y. Suppose there are five observations, A through E. Among them, firms B and C are, relatively speaking, the most efficient ones (since they utilize the least input combinations to produce the same level of output), and hence, they are used to establish the piece-wise linear convex isoquant frontier SS.

On the contrast, firm A is technically inefficient and ideally, wants to move as close to the frontier SS as possible. As such, point F on the frontier SS would become the target for firm A, and the distance AF can be treated as its technical inefficiency. A better definition, however, uses the ratio of AF/AO to represent technical inefficiency and FO/AO (1 − AF/AO) to represent technical efficiency. The merit of using the ratio measures for technical (in)efficiency is that they are unit independent: the change in measurement units does not affect the (in)efficiency scores [14]. This ratio score of efficiency will result in a value from the range of 0 to 1, and a higher score indicates a higher technical efficiency. Based on this definition, it is noted that firms B and C have perfect technical efficiency scores, because both lie on the nonparametric production frontier.

2.2. Research methodologies and hypothesis

Data envelopment analysis (DEA) is a linear programming model for constructing the nonparametric production frontier and measuring technical efficiency. DEA was initiated by Charnes, Cooper, and Rhodes (CCR) [12], and their original model assumed constant returns to scale in the production process. Banker, Charnes, and Cooper (BCC) [4] later proposed an alternative model that can handle the more flexible case of variable returns to scale. In the first stage of our study, the BCC model is employed to measure the technical efficiency scores for the firms in the data set. The detailed formulation of the BCC model for our study is presented in Appendix A.

Technical inefficiency in a production process are attributed to a number of events that would unfavorably affect the firm's capacity to transform input resources into output. Some of the undesirable events are beyond the firm's control, like weather, natural disasters, accidents, regulation changes, etc. Others, however, can be ascribable to the firm itself and be amended through efforts to rectify the situation. Examples of these include information overload, inefficient resource allocation, poor communication, uninformed decision making, etc. The integration of IT into the various activities of the production process presumably is able to palliate or eliminate some rectifiable causes for technical inefficiency.

For instance, executive information systems gather, compile, and process data retrieved from various sources to present useful summary information to top management, who then can make sound decisions. Distributed databases connect geographically dispersed business units and share information in a timely fashion to promote better allocation and efficient utilization of organizational resources. Computer networks help transfer messages quickly among the employees in an organization, overcome distance and time zone differences, and facilitate effective communication. AI-based information agents sift the fetched information, and hence, are able to help users cope with the issue of information overload.

As a consequence, there are reasons for us to presume that the deployment of IT in an organization is able to enhance its capability to produce more output using the same amount of input or, alternatively, produce the same level of output using less input. Therefore, the following hypothesis is implied.

Hypothesis 1. A firm's IT spending has a favorable impact on the technical efficiency of its production process.

In order to examine IT's impact on technical efficiency in the production process, we carry on the second stage of our study by regressing the scores of technical efficiency, derived from DEA in the first stage, against their respective IT investments. Nevertheless, some firms that are, relatively speaking, the most efficient in comparison with the others are employed to construct the nonparametric production frontier. Hence, they have perfect scores of one for their efficiency measurement.

McCarty and Yaisawarng [36] suggest that, under this circumstance, the Tobit regression model should be used, because it can account for the censoring of the dependent variable. When the dependent variable is censored, values in a certain range (>1 in our case) are transformed to a particular value (one in our case). If, for firm i, we represent the original scores of technical efficiency as TE_i^*, the measured (censored) scores of technical efficiency by DEA as TE_i, and IT spending as I_i, then the Tobit regression model in the second stage of our study is formulated as:

$$\mathrm{TE}_i^* = \alpha_0 + \alpha_I I_i + \varepsilon_i,$$
$$\mathrm{TE}_i = 1, \text{if } \mathrm{TE}_i^* \geq 1,$$
$$\mathrm{TE}_i = \mathrm{TE}_i^*, \text{if } \mathrm{TE}_i^* < 1, \quad i = 1, \ldots, n.$$

When the coefficient estimate α_I for IT investments is found to be significantly positive, we are provided with statistical evidence to corroborate that IT exerts a positive total effect on the firm's technical efficiency in the production process. Details of the Tobit regression model are discussed further in Appendix B.

3. Data description

A comprehensive firm-level data set is employed in our study. This data set was used in several previous studies to examine the effects of IT on productivity, profitability, consumer value, and substitution elasticities.

The data on IT expenditures were collected from IDG/Computerworld surveys of Fortune 500 firms, conducted annually from 1988 to 1992. Among the firms that responded to the surveys, about two-third were from the manufacturing sector, with the rest from the service sector. The IT-related data were supplemented by the Standard & Poor's Compustat II database for other data, including output, capital, labor, and other financial indexes. To rule out the effects of inflation, appropriate deflators gathered from various sources were used to convert the monetary values into constant 1990 dollars. Altogether, the data set consisted of 1115 observations from 370 different firms during the 5-year period and thus, it is incomplete with 735 missing data points.

A firm's value-added output (Y) is defined as its gross sales deflated by the industry output price deflators [10], minus its non-labor expenses deflated by the producer price index for intermediate materials, supplies and components [15]. Two production factors, capital (K) and labor (L), were computed as book values of capital stock and labor expenses. They were deflated by the GDP deflator for fixed investment and the price index for total compensation, respectively.

The IT-related data were in two parts: IT hardware value and IS staff expenses. Acquired from the IDG annual survey, IT hardware value (H) is defined as the market value of central processors plus the estimated value of PCs and terminals. It was deflated by the computer price deflator [21]. The variable of IS staff expenses (S) was derived as the labor portion of the IS budget from the survey and then was deflated by the labor price.

IT spending (I) was constructed by aggregating H and S. The apparent way of doing this was to add them and use the total to represent the IT spending variable. Previous research, however, contended that S stands for a class of expenditures that create valuable capital assets (e.g. software programs) with a life span of several years; accordingly, S needs to be given some weight in the formulation of I. This line of research assumed an average of 3 years for those capital assets but suggested a possible range of 1 year (as an annual expense) to 7 years (as the life of computer hardware assumed by the Bureau of Economic Analysis). To follow this suggestion, we considered the variable of IT spending as the sum of IT hardware value and one to seven times IS staff expenses ($I = H + mS$, $m = 1, \ldots, 7$). The sample statistics for the variables are presented in Table 1, with $I = H + S$.

Table 1
Sample summary statistics in 1990 dollars (dollar figures in millions)

Variable	Average per firm	S.D.	As % of value-added output
Value-added output (Y)	3087.0	4615.0	100.0
Capital (K)	8732.0	13440.0	282.0
Labor (L)	1788.0	2845.0	57.9
IT hardware value (H)	109.7	249.6	3.6
IS staff expenses (S)	59.6	134.8	1.9
IT spending ($I = H + S$)	169.3	356.1	5.5
Capital (K), excluding H	8621.0	13320.0	279.0
Labor (L), excluding S	1728.0	2731.0	55.9

In conducting this research, we also considered two cases of production factor categorization. For the first, the inputs engaged in DEA modeling included the traditional production factors: capital and labor. Thus, IT hardware value was part of capital, and IS labor expenses were included in labor. IT spending was then thought of as an observable firm-specific factor, which influences the firm's capacity of converting inputs into output in the production process. This kind of input categorization has been used in production economics studies to investigate how technical efficiency is related to such firm-specific characteristics as age, size, firm ownership, import-substitution versus export orientation, etc. (e.g. [13,43,44]).

On the other hand, several recent studies of IT economic value have treated IT spending as an individual production factor, in an attempt to examine IT's marginal product and net substitution for other inputs. Thus, for the second case of categorization, we also excluded IT hardware value and IS labor expenses from capital and labor, and considered IT spending as a separate production factor in measuring technical efficiency through DEA. The Tobit regression model then followed to determine the correlation between IT spending and technical efficiency.

It should be pointed out that the same production technologies are assumed to represent the production frontiers for the data set when the BCC model of DEA

Table 2
Results of the BCC model with IT spending as a firm-specific factor[a]

Year	Average TE	Average SE	No. of observations	No. of TE = 1
1988	0.785	0.951	137	17
1989	0.787	0.938	133	17
1990	0.775	0.946	262	30
1991	0.759	0.911	287	25
1992	0.765	0.915	296	25
All	0.735	0.915	1115	31

[a] TE: technical efficiency; SE: scale efficiency.

is formulated in the first stage. This assumption is consistent with previous studies on productivity, which were based on the same data set. More justification of applying DEA to a wide range of industries can be found in Arcelus and Arozena's study [2] devoted to examining the productivity and efficiency of 14 countries.

4. Results and discussions

4.1. IT spending as a firm-specific factor

When IT spending is treated as an observed firm-specific characteristic, we are interested in the sign and significance level of the coefficient estimate of α_I in the Tobit regression model. The results from the first stage of DEA for this categorization of production factors (K and L) are presented in Table 2. The BCC model assumes variable returns to scale, and computes the scores of technical efficiency (TE) and scale efficiency (SE) for each firm in the data set. The averages of both efficiencies are presented. Also the numbers of firms with technical efficiency scores equal to 1 (i.e. those firms which are, comparatively speaking, the most efficient) are reported. They are used to construct the nonparametric production frontiers for the measurement of technical efficiency.

Table 3 shows the coefficient estimates of α_I from the Tobit regression model in the second stage. It is observed that all of the coefficient estimates of α_I are significantly positive with the $p < 0.01$ (actually most of them with the $p < 0.001$). Therefore, we are able to reject the null hypothesis, or the alternative hypothesis of Hypothesis 1 is not rejected, with a confidence level of 99%. In other words, the conclusion represents strong statistical evidence that IT investments, considered as a firm-specific factor, exert a positive total effect on the firm's technical efficiency in the production process.

4.2. IT spending as a production factor

In the second categorization, IT spending is regarded as a production factor, along with capital and labor, in the production process for efficiency measurement. This categorization of production factors followed several related studies that were based on the same data set. The coefficient estimate of α_I in the Tobit regression model reveals the correlation between IT spending and technical efficiency. For every value of m (1, ..., 7) used in aggregating IT

Table 3
Estimates of α_I with IT spending as a firm-specific factor[a]

Year	m						
	1	2	3	4	5	6	7
1988	0.243** (0.088)	0.175** (0.066)	0.137** (0.053)	0.112** (0.043)	0.095** (0.036)	0.082** (0.031)	0.072** (0.028)
1989	0.196** (0.060)	0.135** (0.042)	0.101** (0.032)	0.081** (0.026)	0.067** (0.022)	0.057** (0.019)	0.050** (0.016)
1990	0.155*** (0.041)	0.111*** (0.030)	0.086*** (0.023)	0.069*** (0.019)	0.058*** (0.016)	0.050*** (0.014)	0.044*** (0.012)
1991	0.126*** (0.028)	0.096*** (0.020)	0.077*** (0.016)	0.063*** (0.013)	0.054*** (0.011)	0.047*** (0.010)	0.041*** (0.009)
1992	0.082** (0.025)	0.066*** (0.019)	0.054*** (0.015)	0.046*** (0.013)	0.040*** (0.011)	0.035*** (0.009)	0.031*** (0.008)
All	0.072*** (0.011)	0.058*** (0.008)	0.047*** (0.007)	0.040*** (0.005)	0.034*** (0.005)	0.030*** (0.004)	0.026*** (0.004)

[a] S.D. are given in parentheses.
** $p < 0.01$.
*** $p < 0.001$.

Table 4
Results of the BCC model with IT spending as a production factor ($m = 3$)[a]

Year	Average TE	Average SE	No. of observations	No. of TE = 1
1988	0.812	0.947	137	26
1989	0.840	0.962	133	31
1990	0.798	0.950	262	31
1991	0.794	0.924	287	40
1992	0.792	0.945	296	43
All	0.759	0.938	1115	64

[a] TE: technical efficiency; SE: scale efficiency.

spending, different scores of efficiency were derived by the BCC model. Table 4 shows only the results for $m = 3$, mainly because this value has been used in most of prior research. Since the results for the other values of m are quite similar, they are omitted for the sake of brevity. The scores of technical efficiency in Table 4 are higher than those in Table 2. These results correspond to one feature of DEA, which states that the addition of an extra input in a DEA model results in an increase in the scores of technical efficiency.

The estimates of α_I from the Tobit regression model in the second stage are presented in Table 5. All the coefficient estimates of α_I are observed significantly positive with the $p < 0.05$ (actually most with the $p < 0.01$), thereby allowing us to reject the null hypothesis with a confidence level of 95%. We are again provided with significant results to support our thesis that IT spending, regarded as a production factor here, exercises a favorable impact on the firm's technical efficiency in the production process.

4.3. Discussions

The empirical results presented above are robust and consistent because different values for the service life of capital assets created by IS staff expenses were assumed and two input categorizations were also considered in measuring the scores of technical efficiency through the BCC model. In general, IT is expected to enhance the firm's technical efficiency in its production process.

Moreover, the estimated total effects of IT spending on technical efficiency are found to decrease when the value assumed for m (the multiplier for S in the formulation of I) increases. The average decrease rate is 16.74% when IT spending is treated as a firm-specific factor, and 17.55% when IT spending is considered as a production factor. As m increases, the IS labor component of IT spending becomes more intensive (or the hardware capital component becomes less intensive). This tendency corresponds with the claim made by production economics researchers that technical efficiency and capital intensity commonly are positively correlated [51]. The rationale for promoting a capital-intensive production process is that labor-intensive alternatives would require more labor and at the same time, more capital per output unit, compared with those production technologies with high capital–labor proportions.

It has also been noted that when labor costs are continually rising and hardware costs dramatically

Table 5
Estimates of α_I with IT spending as a production factor[a]

Year	m						
	1	2	3	4	5	6	7
1988	0.181* (0.085)	0.128* (0.060)	0.098* (0.047)	0.079* (0.039)	0.066* (0.033)	0.056* (0.028)	0.049* (0.025)
1989	0.079* (0.040)	0.060* (0.030)	0.047* (0.023)	0.037* (0.018)	0.031* (0.015)	0.024* (0.012)	0.021* (0.010)
1990	0.132** (0.044)	0.094** (0.031)	0.072** (0.024)	0.058** (0.019)	0.048** (0.016)	0.041** (0.014)	0.036** (0.012)
1991	0.121*** (0.031)	0.091*** (0.022)	0.071*** (0.018)	0.058*** (0.014)	0.049*** (0.012)	0.042*** (0.011)	0.037*** (0.009)
1992	0.080** (0.028)	0.066** (0.021)	0.056*** (0.017)	0.047*** (0.014)	0.041*** (0.012)	0.036*** (0.010)	0.033*** (0.009)
All	0.069*** (0.012)	0.055*** (0.009)	0.045*** (0.007)	0.037*** (0.006)	0.032*** (0.005)	0.028*** (0.004)	0.025*** (0.004)

[a] S.D. are given in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

falling, the firm should make good use of this cost advantage associated with hardware [25]. This suggests that in an efficient production process the hardware cost advantage should be capitalized by replacing some labor with hardware, hence, intensifying the hardware component in IT investments.

4.4. Practical implications

IT, in general, is expected to enhance an organization's performance as measured by technical efficiency. Previous studies of IT economic value have substantiated the positive correlation between IT investment and a firm's productivity growth and thus, suggested that the IT productivity paradox had disappeared. Due to the connection between productivity and technical efficiency, if management wishes to improve the firm's productivity, one logical way of achieving this is to employ IT in different aspects of the business and enhance its technical efficiency in the production process.

However, management should not draw too hasty a conclusion from our findings. The positive relationship between IT and technical efficiency does not translate directly into reckless IT investments. Firms that invest heavily in IT and are highly efficient in the production process may differ inherently from inefficient firms in ways that are not rectifiable by merely increasing IT expenditure. Strong support from top management, effective IT strategies, innovative organizational culture, excellent IT personnel, and other resources must also be available to help exploit this promised benefit of IT.

4.5. Spurious correlation

In the two-stage procedure, technical efficiency is measured as a function of variables that incorporate or include IT investments; then technical efficiency is regressed against IT investments. This two-stage process might lead to a danger of spurious correlation.

In econometrics [24,28], spurious correlation is known to arise from the transformation of mutually uncorrelated variables into correlated (values of the) ratios of the mutually uncorrelated variables, or from the fact that a common trend is present in the dependent variable and one or more of the independent variables. In our study, we did not encounter such situations. Moreover, it is permissible that a variable (technical efficiency in our case) appears in two places (equations) in a model (e.g. [29,47]). Thus, we are not concerned with the problem of spurious correlation in the statistical analysis.

5. Conclusions

This paper has focused on the relationship between IT investments and technical efficiency in the firm's production process and employed a two-stage analytical investigation, DEA and the Tobit regression model. We have obtained statistical evidence suggesting that IT, in general, exerts a significantly positive influence on the firm's technical efficiency. Due to the close relationship between technical efficiency and productivity, this study offers another way to explain the productivity paradox associated with IT.

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Appendix A. The BCC model for the first stage study

In this research, there are several inputs X_i (capital and labor, plus an optional IT spending) and one output Y. For any specific firm k, the CCR model with constant returns to scale can be formulated as follows to obtain its score of technical efficiency (where n is the number of firms, and s is the number of inputs):

- CCR

$$\text{Maximize}\, u_k Y_k,$$

$$\text{subject to} \begin{cases} u_k Y_j - \sum_{i=1}^{s} v_{ik} X_{ij} \leq 0, \; j = 1, \ldots, n, \\ \sum_{i=1}^{s} v_{ik} X_{ik} = 1, \\ u_k \geq 0, \\ v_{ik} \geq 0, \quad i = 1, \ldots, s. \end{cases}$$

Using the duality in linear programming, we can derive an equivalent envelopment form for this problem. The envelopment form involves fewer constraints than the CCR formulation and is thus preferred for programming. The dual form is formulated as follows:

- Dual

Minimize q_k,

$$\text{subject to} \begin{cases} -Y_k + \sum_{j=1}^{n} p_{kj} Y_j \geq 0, \\ q_k X_{ik} - \sum_{j=1}^{n} p_{kj} X_{ij} \geq 0, \quad i = 1, \ldots, s, \\ p_{kj} \geq 0, \quad j = 1, \ldots, n, \\ q_k \text{ unrestricted in sign.} \end{cases}$$

To relax the assumption of constant returns to scale inherent in the CCR model, an additional convexity constraint, $\sum_j p_{kj} = 1$, is added to the dual model. This convexity constraint makes sure that an inefficient firm is only compared with the firms of a similar size, and the target for that firm on the nonparametric production frontier is a convex combination of the most efficient firms utilized to construct the frontier. This BCC model constructs a convex hull of intersecting planes which enclose the data points more tightly than the CCR hull and thus, generates technical efficiency scores greater than or equal to those obtained using the CCR model. In our first stage study, the BCC model, which can handle variable returns to scale, is formulated to measure the scores of technical efficiency as follows:

- BCC

Minimize q_k,

$$\text{subject to} \begin{cases} -Y_k + \sum_{j=1}^{n} p_{kj} Y_j \geq 0, \\ q_k X_{ik} - \sum_{j=1}^{n} p_{kj} X_{ij} \geq 0, \quad i = 1, \ldots, s, \\ \sum_{j=1}^{n} p_{kj} = 1, \\ p_{kj} \geq 0, \quad j = 1, \ldots, n, \\ q_k \text{ unrestricted in sign.} \end{cases}$$

Appendix B. The Tobit regression model for the second stage study

Suppose the original scores of technical efficiency TE_i^* has a normal distribution $N(\mu, \sigma^2)$. The measured (censored) scores of technical efficiency TE_i, derived from the BCC model of DEA in the first stage, is equal to 1 if $\mathrm{TE}_i^* \geq 1$, or $\mathrm{TE}_i = \mathrm{TE}_i^*$ otherwise. Then from [1,22]:

$$E[\mathrm{TE}] = (1 - \Phi) + \Phi(\mu + \sigma\lambda),$$
$$Var[\mathrm{TE}] = \sigma^2 \Phi[(1 - \delta) + (\alpha - \lambda)^2 (1 - \Phi)],$$

where $\Phi((1 - \mu)/\sigma) = \Phi(\alpha) = \mathrm{Prob}(\mathrm{TE}_i^* \leq 1) = \Phi$, $\lambda = -\phi/\Phi$, and $\delta = \lambda^2 - \lambda\alpha$; Φ and ϕ are the cumulative distribution function and probability density function for $N(0, 1)$, respectively.

In the second stage, the Tobit regression model is formulated as follows:

$$\mathrm{TE}_i^* = \alpha_0 + \alpha_I I_i + \varepsilon_i,$$
$$\mathrm{TE}_i = 1, \text{ if } \mathrm{TE}_i^* \geq 1,$$
$$\mathrm{TE}_i = \mathrm{TE}_i^*, \text{ if } \mathrm{TE}_i^* < 1, \quad i = 1, ..., n.$$

If $\varepsilon_i \sim N(0, \sigma^2)$, then $E[\mathrm{TE}_i | I_i] = [1 - \Phi((1 - \alpha_0 - \alpha_I I_i)/\sigma)] + \Phi((1 - \alpha_0 - \alpha_I I_i)/\sigma))(\alpha_0 + \alpha_I I_i + \sigma\lambda_i)$, where $\lambda_i = -\phi((1 - \alpha_0 - \alpha_I I_i)/\sigma)) / \Phi((1 - \alpha_0 - \alpha_I I_i)/\sigma))$, and $E[\mathrm{TE}_i^* | I_i] = \alpha_0 + \alpha_I I_i$. The marginal effects are estimated by

$$\frac{\partial E[\mathrm{TE}_i | I_i]}{\partial I_i} = \Phi\left(\frac{1 - \alpha_0 - \alpha_I I_i}{\sigma}\right)\alpha_I,$$
$$\frac{\partial E[\mathrm{TE}_i^* | I_i]}{\partial I_i} = \alpha_I.$$

References

[1] T. Amemiya, Regression analysis when the dependent variable is truncated normal, Econometrica 41 (6), 1973, pp. 997–1016.

[2] F.J. Arcelus, P. Arozena, Measuring sectoral productivity across time and across countries, European Journal of Operational Research 119 (2), 1999, pp. 254–266.

[3] J.Y. Bakos, A strategic analysis of electronic marketplaces, MIS Quarterly 15 (3), 1991, pp. 295–310.

[4] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, Management Science 30 (9), 1984, pp. 1078–1092.

[5] R.D. Banker, R.J. Kauffman, R.C. Morey, Measuring gains in operational efficiency from information technology: a study of the Positran deployment at Hardee's Inc., Journal of Management Information Systems 7 (2), 1990, pp. 29–54.
[6] A. Barua, C.H. Kriebel, T. Mukhopadhyay, Information technologies and business value: an analytical and empirical investigation, Information Systems Research 6 (1), 1995, pp. 3–23.
[7] D.H. Bender, Financial impact of information processing, Journal of Management Information Systems 3 (2), 1986, pp. 22–32.
[8] E. Brynjolfsson, The productivity paradox of information technology, Communications of the ACM 36 (12), 1993, pp. 66–77.
[9] E. Brynjolfsson, L. Hitt, Paradox lost? Firm-level evidence on the returns to information system spending, Management Science 42 (4), 1996, pp. 541–558.
[10] Bureau of Economic Analysis, Fixed Reproducible Tangible Wealth in the United States, US Department of Commerce, Washington, DC, 1993.
[11] A.L.M. Cavaye, User participation in system development revisited, Information and Management 28 (5), 1995, pp. 311–323.
[12] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, European Journal of Operational Research 2 (6), 1978, pp. 429–444.
[13] T. Chen, D. Tang, Comparing technical efficiency between import-substitution-oriented and export-oriented foreign firms in a developing economy, Journal of Development Economics 26 (2), 1987, pp. 277–289.
[14] T. Coelli, D.S.P. Rao, G.E. Battese, An introduction to efficiency and productivity analysis, Kluwer Academic Press, Norwell, MA, 1998.
[15] Council of Economic Advisors, Economic Report to the President, Government Printing Office, Washington, DC, 1992.
[16] W.L. Cron, M.G. Sobol, The relationship between computerization and performance: a strategy for maximizing the economic benefits of computerization, Information and Management 6 (3), 1983, pp. 171–181.
[17] T.H. Davenport, Information Ecology, Oxford University Press, New York, 1997.
[18] S. Dewan, C. Min, The substitution of information technology for other factors of production: a firm-level analysis, Management Science 43 (12), 1997, pp. 1660–1675.
[19] B.L. Dos Santos, Justifying investments in new information technologies, Journal of Management Information Systems 7 (4), 1991, pp. 71–90.
[20] S.W. Floyd, B. Wooldridge, Path analysis of the relationship between competitive strategy, information technology, and financial performance, Journal of Management Information Systems 7 (1), 1990, pp. 47–64.
[21] R.J. Gordon, The Measurement of Durable Goods Prices, University of Chicago Press, Chicago, IL, 1991.
[22] W.H. Greene, Econometric Analysis, 2nd Edition, Macmillan, New York, 1993.
[23] S. Grosskopf, Efficiency and productivity, in: H.O. Fried, C.A.K. Lovell, S.S. Schmidt (Eds.), The Measurement of Productive Efficiency: Techniques and Applications, Oxford University Press, New York, 1993, pp. 160–194.
[24] D. Gujarati, Basic Econometrics, McGraw-Hill, New York, 1978.
[25] V. Gurbaxani, K. Kraemer, N. Vitalari, Note: an economic analysis of IS budgets, Management Science 43 (12), 1997, pp. 1745–1755.
[26] L.M. Hitt, E. Brynjolfsson, Productivity, business profitability, and consumer surplus: three different measures of information technology value, MIS Quarterly 20 (3), 1996, pp. 121–142.
[27] L.M. Hitt, Information technology and firm boundaries: evidence from panel data, Information Systems Research 10 (2), 1999, pp. 134–149.
[28] L.R. Klein, A Textbook of Econometrics, Prentice-Hall, Englewood Cliffs, NJ, 1974.
[29] W.T. Lin, Analysis of lumber and pulpwood production in a partial adjustment model with dynamic and variable speeds of adjustments, Journal of Business and Economic Statistics 4 (3), 1986, pp. 305–316.
[30] W.T. Lin, B.B.M. Shao, The relationship between user participation and system success: a simultaneous contingency approach, Information and Management 37 (6), 2000, pp. 283–295.
[31] W.T. Lin, B.B.M. Shao, Relative sizes of information technology investments and productive efficiency: their linkage and empirical evidence, Journal of the Association for Information Systems 1 (7), 2000, pp. 1–35.
[32] F. Lichtenberg, The output contributions of computer equipment and personnel: a firm level analysis, Economics of Innovation and New Technology 3 (4), 1995, pp. 201–217.
[33] C.A.K. Lovell, Production frontiers and productive efficiency, in: H.O. Fried, C.A.K. Lovell, S.S. Schmidt (Eds.), The Measurement of Productive Efficiency: Techniques and Applications, Oxford University Press, New York, 1993, pp. 3–67.
[34] G.W. Loveman, An assessment of the productivity impact of information technologies, in: T.J. Allen, M.S. Scott Morton (Eds.), Information Technology and the Corporation of the 1990s: Research Studies, MIT Press, Cambridge, MA, 1994, pp. 84–110.
[35] M.A. Mahmood, G.J. Mann, Measuring the organizational impact of information technology investment: an exploratory study, Journal of Management Information Systems 10 (1), 1993, pp. 97–122.
[36] T.A. McCarty, S. Yaisawarng, Technical efficiency in New Jersey school districts, in: H.O. Fried, C.A.K. Lovell, S.S. Schmidt (Eds.), The Measurement of Productive Efficiency: Techniques and Applications, Oxford University Press, New York, 1993, pp. 271–287.
[37] S. Mitra, A.K. Chaya, Analyzing cost-effectiveness of organizations: the impact of information spending, Journal of Management Information Systems 13 (2), 1996, pp. 29–57.

[38] C.J. Morrison, E.R. Berndt, Assessing the productivity of information technology equipment in the US manufacturing industries, National Bureau of Economic Research, Working Paper No. 3582, Cambridge, MA, 1991.
[39] T. Mukhopadhyay, R.B. Cooper, A microeconomic production assessment of the business value of management information systems: the case of inventory control, Journal of Management Information Systems 10 (1), 1993, pp. 33–55.
[40] T. Mukhopadhyay, S. Kekre, S. Kalathur, Business value of information technology: a study of electronic data interchange, MIS Quarterly 19 (2), 1995, pp. 137–156.
[41] T. Mukhopadhyay, S. Rajiv, K. Srinivasan, Information technology impact on process output and quality, Management Science 43 (12), 1997, pp. 1645–1659.
[42] T. Mukhopadhyay, F.J. Lerch, V. Mangal, Assessing the impact of information technology on labor productivity: a field study, Decision Support Systems 19 (2), 1997, pp. 109–122.
[43] M.M. Pitt, L.F. Lee, The measurement and sources of technical inefficiency in the Indonesian weaving industry, Journal of Development Economics 9 (1), 1981, pp. 43–64.
[44] D. Reifschneider, R. Stevenson, Systematic deviation from the frontier: a framework for the analysis of firm inefficiency, International Economic Review 32 (3), 1991, pp. 715–723.
[45] D.S.J. Remenyi, A. Money, A. Twite, A Guide to Measuring and Managing IT Benefits, Blackwell, Oxford, UK, 1991.
[46] P. Schmidt, Frontier production functions, Econometric Reviews 4 (2), 1986, pp. 289–328.
[47] B.B.M. Shao, W.T. Lin, Examining the determinants of productive efficiency with IT as a production factor, Journal of Computer Information Systems 41 (1), 2000, pp. 25–30.
[48] P.A. Strassmann, The Business Value of Computers, Information Economics Press, New Canaan, CT, 1990.
[49] J. Tobin, Estimation of relationships for limited dependent variables, Econometrica 26, 1958, pp. 24–36.
[50] P. Weill, The relationship between investment in information technology and firm performance: a study of the valve manufacturing sector, Information Systems Research 3 (4), 1992, pp. 304–333.
[51] L.J. White, The evidence of appropriate factor proportions for manufacturing in less developed countries: a survey, Economic Development and Cultural Change 27 (1), 1978, pp. 27–59.
[52] L.P. Willcocks, S. Lester, Beyond the IT Productivity Paradox, Wiley, Chichester, UK, 1999.

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