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Relative Sizes of Information Technology Investments and Productive Efficiency: Their Linkage and Empirical Evidence[1]

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Abstract

The contribution of information technology (IT) to organizational performance has been investigated extensively in recent IS research. A number of economic and financial measures have been employed by researchers to gauge the impact of IT

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on organizational performance. The results of previous research can be described as inconclusive at best. This paper uses stochastic frontiers to examine the relationship between the relative size of IT investments by firms and their productive efficiency in the production process.

Assuming different production frontiers (including the popular generalized Cobb-Douglas, the more general Box-Cox transformation, and the most general Box-Tidwell transformation for the production process), we find consistent empirical evidence that the relative level of IT investments has a positive effect on the firm’s productive efficiency, implying that firms investing comparatively more in IT are likely to be more efficient in their production processes than those investing less. This study confirms the positive effect of IT on the firm's efficiency in the production process, provides a source to explain the disappearance of the productivity paradox, and suggests a direction for future research that may integrate both economic and financial aspects of previous research on IT benefits.

Keywords: IT value, productive efficiency, production theory, production functions, stochastic frontiers, computers, IT investments, information system evaluation.

I. INTRODUCTION

Information technology (IT) has changed the way firms currently conduct business and the pace of change is expected to continue to increase in the future. Enormous resources have been allocated for IT by managers to purchase state-of-the-art hardware equipment, to develop new application systems for reengineering business processes, to build up computer networks for connecting suppliers and customers, and to train the IS staff and end-users to become more skilled in using IT. It has been estimated that approximately three trillion dollars have been spent on IT investments in the U.S. over the last decade (Davenport 1997).

Faced with such a spectacular and still-increasing level of IT spending, top management has become concerned with IT payoff. Decisions to invest extensively in IT are made based on the benefits promised by IT, such as enhanced capability, coordinated control, improved communication, and competitive advantages (Senn 1989). However, such intangible benefits are usually hard to quantify for measurement and, hence, great difficulty has been encountered when the issue of IT value needs to be addressed. As such, it has become essential to find evidence that can justify such expensive IT investments (Dos Santos 1991).

At the same time, researchers interested in the impact of IT on organizational performance have reported their findings incessantly over the last two decades. The measures of organizational performance frequently studied for IT benefits include *profitability* (Bender 1986; Cron and Sobol 1983; Dos Santos 1991; Dos Santos et al. 1993; Floyd and Wooldridge 1990; Hitt and Brynjolfsson 1996; Strassmann 1990; Weill 1992), *productivity* (Dewan and Min 1997; Hitt and Brynjolfsson 1996; Lichtenberg 1995; Loveman 1994; Morrison and Berndt 1991; Mukhopadhyay and Cooper 1993; Mukhopadhyay et al. 1997a; Weill 1992), *costs* (Alpar and Kim 1990; Mitra and Chaya 1996; West 1994), *quality* (Mukhopadhyay et al. 1997b), *operative efficiency* (Banker et al. 1990), and *consumer surplus* (Bresnahan 1986; Hitt and Brynjolfsson 1996).

Some of the studies were able to confirm the contribution of IT, while others still obtained weak or even inconclusive results. For instance, the so-called productivity paradox of IT (Baily and Gordon 1988; Roach 1991) puzzled both managers and researchers during the 1980s and is claimed to have disappeared in the early 1990s (see, e.g., Hitt and Brynjolfsson 1996). The results of these studies on IT business value are said to be inconclusive at best (Mukhopadhyay et al. 1997b).

Looking at a different performance measure called *productive* (or *technical*) *efficiency*, which has been rarely studied in the context of IT value, this paper investigates the impact of IT investments on the firm's performance in the production process. Banker et al. (1990) employed a data envelopment analysis (DEA) and a nonparametric production frontier to investigate the effect of IT on operational efficiency in a fast-food chain and concluded that restaurants that had deployed IT were less likely to be inefficient (even though only weak evidence was found in their study when just one of the six hypotheses tested was significantly confirmed). Using a parametric approach of stochastic production frontiers applied to a more comprehensive firm-level data set, we find empirical results that can serve as evidence that the relative size of IT spending has a favorable influence on the firm's productive efficiency in the production process.

In the following, note that productivity growth is also called dynamic efficiency and productive efficiency is also referred to as static efficiency. The use of productive efficiency to evaluate the business value of IT investments is motivated by a number of reasons.

First, according to the tests conducted by Caves and Barton (1990), Fecher and Perelman (1992), and Lin and Chen (1999), among others, productive efficiency exerts a positive effect on productivity growth; that is, productive inefficiency is hostile to productivity growth. They have explored the consequences of productive inefficiency by inquiring whether productive inefficiency impairs a firm's or an industry's ability to attain productivity growth, and argued that the question raises issues of sufficient potential importance to warrant an inquiry about the organizational performance in terms of productive (in)efficiency.

Second, McKeen and Smith (1993) have attributed the relatively modest success of IT value research to the fact that there is no single, well-established measure of organizational performance. It is suggested that the measurement of organizational performance really depends on what constituency the researcher is trying to address (Zammuto 1982). Zammuto has suggested some possible measures for IT value: productivity, satisfaction, profit, quality, growth, efficiency, morale, and adaptability. This list of measures obviously is not exhaustive. Although an organization sometimes requires a special measure (for instance, a wellaccepted measure of organizational performance for the firms in the insurance industry is the ratio of non-interest operating expense to premium income [Bender 1986; Harris and Katz 1988]), a measure, like productive efficiency, which can be applied to any type of organization, is preferred. Unlike many other proposed measures, for example, the financial measures (such as earning per share, return on investment, operating expense, pretax profit, and sales), which can only be applied to financial organizations and systems, productive efficiency can be widely applied to all types of organizations (manufacturing and service). Productive efficiency is considered more useful than previously used measures from the organization's perspective.

Third, from the organization's perspective, evaluating the effect of IT investments on organizational performance in terms of efficiency can provide us with insights that previous research has failed to provide simply because it does not use this performance measure. Thus, this study is motivated by lack of research in this literature. In this situation, productive efficiency is both interesting and useful because it has rarely been studied in previous research on the value of IT investments.

Fourth, productive efficiency belongs to the domain of economic analysis. It is closely related to productivity and effectiveness (the relationships between efficiency and productivity and between efficiency and effectiveness will be addressed in a later section), but it is a different economic measure, which indicates how efficiently a firm utilizes inputs in producing output, and bears its own significance for research. The distinction between efficiency and productivity is emphasized in this paper because it serves as one of the motivations for our study and represents the contribution made.

Finally, productive efficiency is an economic index of organizational performance. In assessing IT value, productive efficiency cannot substitute for, nor be substituted for by, other performance measures. On the other hand, it can be analyzed, along with other performance measures, to provide more ample evidence to substantiate the contribution that IT may make.

Thus, it is our belief that an improvement in productive efficiency necessarily leads to an improvement in organizational performance. The present study has one clear message: the application of productive efficiency to analyze the contrasting impacts of IT investments on organizational performance provides a striking example illustrating the importance and usefulness of considering productive efficiency as a performance measure. It should be emphasized that efficiency, although rarely studied in previous research, is as prominent an economic measure as productivity and may provide additional insight into the issue of evaluating and justifying IT investments.

The productivity paradox of IT is that the recent enormous investments in IT have not been found correlated with significant improvement in aggregate output productivity. Not until recently has contrary evidence been found to indicate the disappearance of the productivity paradox, although this is possibly due to differences in sampling and methodologies used. The present study, while focusing on measuring IT contributions to productive efficiency, may also provide suggestions toward explaining the productivity paradox phenomenon, thanks to the close relationship between efficiency and productivity.

The remainder of the paper will be organized as follows. The second section provides the theoretical basis of this study—microeconomic production theory—and the methodology—stochastic frontiers—applied to measuring the productive efficiency of firms with IT investments. The third section specifies the various production functional forms and discusses the characteristics of the firm-level data used for our investigation. The fourth section presents the empirical findings and discusses managerial implications and business guidelines when considering and handling IT investments. Finally, the paper concludes by discussing the limitations and proposing some possible topics for future research.

II. PRODUCTION THEORY AND STOCHASTIC FRONTIERS

PRODUCTION THEORY AND PRODUCTIVE (IN)EFFICIENCY

Production theory in microeconomics suggests that firms utilize various inputs or production factors such as capital, labor, and others, and transform these inputs into output. Such a transformation (production) process can be represented by a production function. The production function specifically identifies the *maximum* quantity of output attainable by employing a certain combination of inputs. Since the production function sets a ceiling (or an ideal) limit on output, it is also referred to as a production frontier. The distance between the ideal and observed (actual) levels of output is then defined as productive (or technical) inefficiency in the process of production.

From a producer's point of view, the existence of productive inefficiency indicates a waste of resources and it should be minimized. Many sources may contribute to productive inefficiency. Physical causes may include the obsolescence of equipment and attrition of the machinery. Behavioral causes may arise from fatigue of workers, mismanagement of resources, or poor judgment by management. No matter what the sources, productive inefficiency is present in the production process to some extent. Management, therefore, should make efforts to measure and minimize productive inefficiency so as to either employ less inputs to produce a given output level or to produce more output with the same usage of inputs.

PRODUCTION THEORY AND STOCHASTIC FRONTIERS

Let Y_{it} be the actual output level produced by firm i at time t, $\mathbf{X}_{it}$ be the set of inputs employed for producing Y_{it}, and $\boldsymbol{\beta}$ be the vector of unknown coefficients (or input elasticities) to be estimated. Then a deterministic production function can be described as

$$Y_{it} = f(\mathbf{X}_{it}; \boldsymbol{\beta}) - u_{it} \tag{1}$$

Deterministic frontiers treat the difference between the ideal output level f($\mathbf{X}_{it}$; $\boldsymbol{\beta}$) and the actual output level Y_{it} as the measured inefficiency u_{it} and do not distinguish a random error component from inefficiency. Such neglect of a random error in deterministic frontiers may cause statistical noise in estimation to be absorbed into inefficiency and, hence, make the measured inefficiency different from what it really is (Schmidt 1985).

Stochastic frontiers, on the other hand, set a stochastic upper bound on output and can be expressed as

$$Y_{it} = f(\mathbf{X}_{it}; \boldsymbol{\beta}) + v_{it} - u_{it} \qquad (i = 1, \ldots, n;\ t = 1, \ldots, N) \tag{2}$$

They clearly acknowledge that the difference between the ideal and actual output levels should be divided into two components: one component for randomness or statistical noise v_{it} and the other for technical inefficiency u_{it}. The random error component v_{it} represents the accumulated effect of the events outside the control of the firm, such as weather, luck, government regulations, foreign exchange rate, and so on. The presence of the random error v_{it} in the production function implies that equation (2) represents a stochastic production frontier. The (in)efficiency component u_{it}, however, reflects the (un)favorable influence of the events under the control of the firm, such as machine obsolescence, poor resource allocation, employee fatigue, and IT mismanagement, and can be improved through continuous organizational efforts.

It is generally believed that stochastic frontiers are a better approach to measuring productive efficiency than deterministic frontiers (Schmidt 1985). The reader may wish to consult Lin and Chen (1999) for a more detailed survey of deterministic and stochastic frontiers. In this study, stochastic production frontiers will be used as the methodology for measuring the firm's productive efficiency.[2]

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[2]The productive (in)efficiency u_{it} may be affected by various factors. To account for this, Lin and Chen (1999) have proposed an equation system described by

$$Y_{it} = f\,(\mathbf{X}_{it}; \boldsymbol{\beta}') + v'_{it} - u'_{it} \tag{a}$$
$$u'_{it} = g(t, \mathbf{z}_{it}; \boldsymbol{\alpha}) + \eta_{it} \tag{b}$$

PRODUCTIVITY VS. EFFICIENCY AND EFFICIENCY VS. EFFECTIVENESS

First, we will distinguish efficiency from productivity and, hence, this study from previous research on productivity (e.g., Hitt and Brynjolfsson 1996; Lichtenberg 1995; Loveman 1994; Morrison and Berndt 1991). As mentioned earlier, productive efficiency is closely related to productivity but is a different economic measure that reflects how efficiently a firm transforms inputs into output. A careful distinction between efficiency and productivity is necessary, because it serves as our motivation to conduct this research and also represents the contribution made by this study.

Efficiency is a concept that pertains to getting the most out of a given set of resources, whereas productivity is a relatively broader concept that pertains to the effective use of overall resources (Stevenson 1999). By definition, productivity denotes an index of output divided by an index of total input usage (or, using the terminologies of economics, it can be defined as the ratio of total revenue to total cost). Productivity growth then refers to the change in productivity over time.

To simplify our discussion (but without loss of generality for the conclusion eventually drawn), suppose a single output measured by lnY is being produced using a single input measured by lnX with the constant returns to scale technology, as shown in Figure 1. The assumed constant returns to scale implies a straight-line production frontier, like OC at time t and OF at time t+1. There are two observations of input and output, B ($\ln X_t$, $\ln Y_t$) and E ($\ln X_{t+1}$, $\ln Y_{t+1}$), for time t and t+1, respectively. Defined as an index of output divided by input, productivity is, therefore, AB/AO and DE/DO, respectively. Efficiency, on the other hand, focuses on the distance of observed output levels from the frontiers and, hence, is measured as AB/AC and DE/DF, respectively.

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where t is the time variable used to serve as the proxy of general economic conditions, $\mathbf{z}_{it}$ represents a broad set of firm-specific factors and factors common to all firms, which lead to the differences in productive efficiency across firms or industries, $\boldsymbol{\alpha}$ is a vector of unknown coefficients to be estimated, η_{it} is the random component of the productive (in)efficiency, which is one-sided normally distributed, and the g function represents the deterministic component of productive (in)efficiency subject to the influences of t and $\mathbf{z}_{it}$.

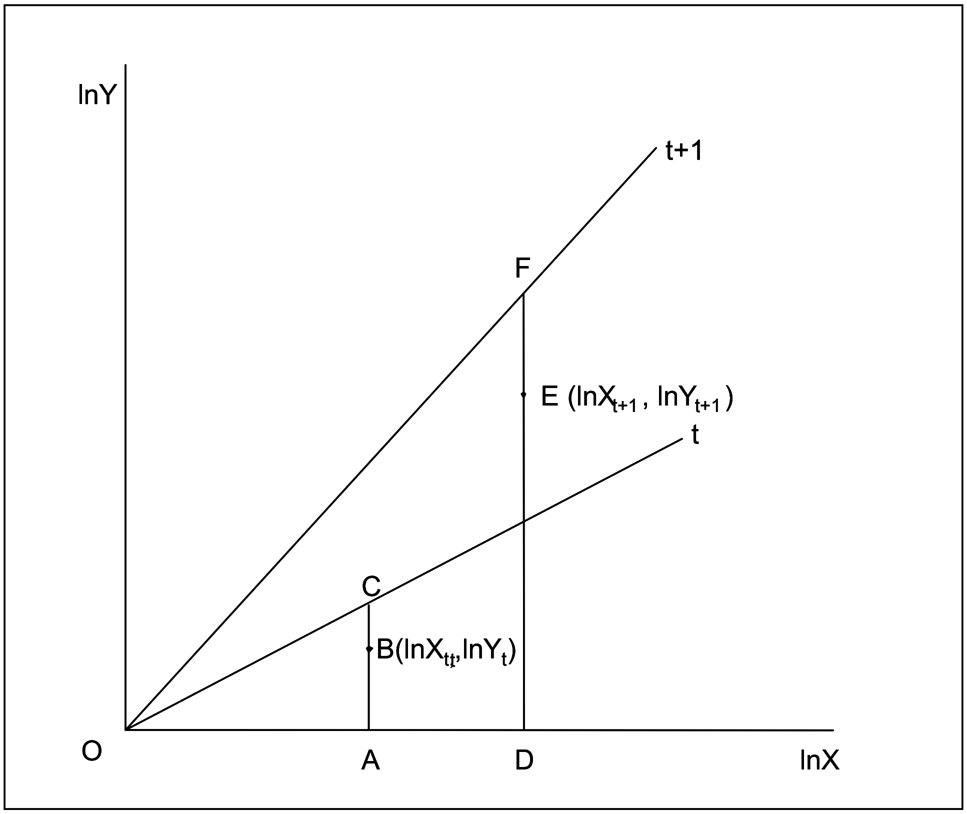

Figure 1. Productivity vs. Efficiency

Productivity growth then can be decomposed as follows:

$$\frac{DE/DO}{AB/AO} = \frac{DE/DF}{AB/AC} \times \frac{DF/DO}{AC/AO}$$

which is equal to the product of the ratio of the efficiency measures and the ratio of the frontier slopes. As a result, productivity growth is a composite index of the change in productive efficiency, (DE/DF)/(AB/AC), and the shift in production frontiers, (DF/OD)/(AC/OA). An important relationship can be established among the three constructs of productivity, efficiency, and technical change (Grosskopf 1993):

Productivity Growth = (Efficiency Change) × (Technical Change)

In other words, productivity growth actually reflects the net effect of efficiency change and technical change.

It should be emphasized that, although efficiency is one component of productivity growth, these two do not have to vary hand in hand. An increase in productivity growth does not necessarily imply an improvement in efficiency and, by the same token, an improvement in efficiency does not always indicate an increase in productivity growth. The reason is that there is technical change, the other component, present in determining productivity growth. It is possible that productivity growth increases due to better technical change while the production is actually becoming less efficient; or the production is carried out more efficiently while productivity deteriorates because of poor technical change. In other words, productivity growth and productive efficiency do not always vary in the same direction. This is the compelling reason why we need to conduct this IT value study on efficiency, differing from previous research on productivity.

On the empirical front, the evidence provided by Caves and Barton (1990), Fecher and Perelman (1992), and Lin and Chen (1999), among others, suggests a possible impact of productive (technical or static) efficiency on productivity growth (or dynamic efficiency).

Next, we are going to distinguish between efficiency and effectiveness. Efficiency is a measure of effectiveness at the system level (Stevenson 1999). According to the production frontier specifications, $Y_{it} = f(\mathbf{X}_{it}; \boldsymbol{\beta}) + v_{it} – u_{it}$, where $\mathbf{X}_{it} = (K_{it}, L_{it}, T_{it})$ with T_{it} being the IT stock of firm i at time t (some details of T_{it} will be given in the next section), the f function is the maximum output that can be possibly attained and, therefore, represents ideal capacity (IC_{it}), and Y_{it} is the actual output (AO_{it}). If we introduce the concept of effective capacity (EC_{it}) being defined as the maximum possible output given machine maintenance, quality factor, scheduling difficulties, and so on (Stevenson 1999, p. 211), then EC_{it} is normally less than IC_{it} because IC_{it} is the maximum rate of output achieved under ideal conditions, and AO_{it} cannot exceed EC_{it} because AO_{it} is the rate of output actually achieved. Thus, EC_{it} acts as a mediator of AO_{it} and IC_{it} and we have the relationship, $AO_{it} \leq EC_{it} \leq IC_{it}$ or $AO_{it} – IC_{it} = -u_{it} \leq EC_{it} – IC_{it} \leq 0$, implying that u_{it} is half-normal.

This relationship has two important implications. First, ignoring the random factor v_{it} that is beyond the control of management, u_{it} (defined as $IC_{it} – AO_{it}$) is ≥ 0 or $-u_{it} \leq 0$. Thus, EC_{it} serves as a lid on AO_{it} and IC_{it} acts as a lid on EC_{it}. Second, improving efficiency is to increase EC_{it} by maintaining plant and equipment in good condition, fully training employees and workers, and fully utilizing IT spending. As a consequence, EC_{it} can be brought closer to IC_{it} and AO_{it} closer to EC_{it}, reducing inefficiency or increasing efficiency. Stated another way, an increase in efficiency or a decline in inefficiency is the result of effective utilization of capacity.

Accordingly, it seems reasonable to conclude that efficiency is a gauge of effectiveness and that (in)efficiency implies (in)effective utilization. The stochastic frontier approach is designed to assess the level of (in)efficiency and, hence, the degree of (in)effectiveness.

III. MODEL AND DATA

SPECIFICATIONS OF STOCHASTIC FRONTIERS

The generalized Cobb-Douglas functional form is one of the most frequently used specifications for production functions, $f(\mathbf{X}_{it}; \boldsymbol{\beta})$ in equation (2). It satisfies the essential requirements for production functions such as quasi-concavity and monotonicity. It is known in the economics literature that a production function of this kind has the virtue of simplicity and empirical validation. Let Y_{it}, K_{it}, L_{it}, and T_{it} represent output, capital, labor, and IT stock for firm i at time t, respectively. Then the nonlinear Cobb-Douglas stochastic frontier can be described as

$$Y_{it} = \alpha K_{it}^{\beta_1} L_{it}^{\beta_2} T_{it}^{\beta_3} e^{v_{it}-u_{it}}, \qquad (i = 1, \ldots, n;\ t = 1, \ldots, N) \qquad (3)$$

or, upon taking logarithm, we have a linear form in terms of double logarithm, i.e., by taking logarithm, the original nonlinear Cobb-Douglas function is transformed into a linear logarithmic function given by

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln T_{it} + v_{it} - u_{it} \qquad (4)$$

where $\beta_0 = \ln\alpha$, $v_{it} \sim N(0, \sigma^2_v)$, and $u_{it} \sim |N(0, \sigma^2_u|$. By definition, the observed (actual) output, Y_{it}, is at most (less than or equal to) the ideal (maximum) output, $f(\mathbf{X}_{it}; \boldsymbol{\beta})$. Consequently, $u_{it} \geq 0$ or $-u_{it} \leq 0$, requiring that u_{it} be half-normal. The one-sided distribution of u_{it} guarantees (in)efficiency to be positive only. Jondrow et al. (1982) have proposed a procedure to obtain the expected value of u_{it}, conditional on $v_{it} - u_{it}$. Productive efficiency is then equal to $e^{-u_{it}}$ and falls in the range between 0 and 1, with a greater value indicating higher efficiency. We will denote the average productive efficiency by AVG, which is defined as $\sum_i \sum_t e^{-u_{it}}/nN$.

Note that the generalized Cobb-Douglas production function, as defined by (3), is originally nonlinear in its factors. Only after taking logarithms will we obtain a linear logarithmic form represented by equation (4) that can be estimated by treating it as a linear regression. The generalized Cobb-Douglas function does not impose any restriction on its coefficients (e.g., constant returns to scale when the coefficients sum to one) and, hence, is able to reflect the inter-relationships between technical change and productive efficiency.

The generalized Cobb-Douglas function is just one specification frequently used in previous research to specify the functional form for a production frontier. To facilitate comparisons and to reach more convincing conclusions, it is both wise and necessary to consider some other general production technological processes. Two of them are the Box-Cox and Box-Tidwell transformations (Lin and Chen 1999). The Box-Cox transformation includes the Cobb-Douglas transformation as a special case, while the Box-Tidwell transformation is a generalization of the Box-Cox transformation.

The stochastic frontier specification of the Box-Cox transformation (Box and Cox 1964) in this study can be specified as

$$\frac{Y_{it}^{\lambda}-1}{\lambda} = \beta_0 + \beta_1\left(\frac{K_{it}^{\lambda}-1}{\lambda}\right) + \beta_2\left(\frac{L_{it}^{\lambda}-1}{\lambda}\right) + \beta_3\left(\frac{T_{it}^{\lambda}-1}{\lambda}\right) + v_{it}-u_{it},\ (i = 1,\ldots,n;\ t = 1,\ldots, N) \qquad (5)$$

In equation (5), the parameter of λ is first obtained using the maximum likelihood method. The maximum likelihood value, L_{max}, is calculated for different values of λ with the following equation:

$$L_{max} = -\left(\frac{nN}{2}\right)\ln\left(\frac{\text{Residual SS}}{nN}\right) + (\lambda - 1)\sum_{i,t}\ln(Y_{it}) \qquad (6)$$

where n is the total number of observations, N is the length of time periods, and SS denotes the sum of squares. The λ that maximizes the L_{max} function of equation (6), denoted by λ^*, is used to transform the data in the Box-Cox model of equation (5). It can be shown that when $\lambda^* = 0$, the Box-Cox transformation of equation (5) reduces to the Cobb-Douglas form of equation (4).

The stochastic frontier of the Box-Tidwell transformation (Box and Tidwell 1962) in this study can be specified as

$$\frac{Y_{it}^{\lambda}-1}{\lambda} = \beta_0 + \beta_1\left(\frac{K_{it}^{\delta}-1}{\delta}\right) + \beta_2\left(\frac{L_{it}^{\delta}-1}{\delta}\right) + \beta_3\left(\frac{T_{it}^{\delta}-1}{\delta}\right) + v_{it} - u_{it}, (i = 1,\ldots,n;\ t = 1,\ldots,N) \quad (7)$$

Similarly, the parameters of λ and δ are obtained using the maximum likelihood method. The maximum likelihood value, L_{max}, is calculated for different values of λ and δ with the following equation:

$$L_{max} = -\left(\frac{nN}{2}\right)\ln\left(\frac{\text{RESIDUAL SS}}{nN}\right) + (\lambda - 1)\sum_{i,t}\ln(Y_{it}) + (\delta - 1)\sum_{i,t}\ln(Y_{it}) \quad (8)$$

where the pair of λ and δ maximizing the L_{max} function, represented by λ^* and δ^*, is used to transform the data in the Box-Tidwell model of equation (7). When $\delta^* = \lambda^*$, the Box-Tidwell transformation becomes identical with the Box-Cox transformation and, when $\delta^* = \lambda^* = 0$, the Box-Tidwell transformation collapses to the Cobb-Douglas function.

DATA

The data used for our study on efficiency are the same as those employed in Hitt and Brynjolfsson's (1996) research on productivity, profitability, and consumer surplus. A main reason to adopt the same data set as used by Hitt and Brynjolfsson and also by Dewan and Min (1997) is to facilitate a comparative analysis so as to rule out the possibility of confusion created by comparing different studies with different data. As such, the findings in this paper can be fairly compared with previous work on the same grounds. Another reason to employ the same data as employed in previous research is that our efforts to secure more current data surveyed by International Data Group (IDG) were unsuccessful as they declined our request for the up-to-date data.

The data source for the IT-related data is the IDG/Computerworld surveys of IS spending by large U.S. corporations, conducted annually during the period 1988 to 1992. The survey focuses primarily on large Fortune 500 firms. About two-thirds of the firms are from the manufacturing sector and the remainder are primarily service firms. Other data on sales, capital investments, labor expenses, and operating income were obtained from Standard & Poor's Compustat II database.

The data were collected from different sources, due mainly to the confidentiality of IT investments spent by companies. Potential problems regarding the data are expected to be present, but the large size of the sample helped mitigate the impact of data errors (Dewan and Min 1997; Hitt and Brynjolfsson 1996). It was also claimed that "the included firms did not appear to differ substantially from the target population in terms of size or profitability measures" (Hitt and Brynjolfsson 1996, p. 129). However, even with these potential problems, the data are still the most comprehensive firm-level data set available for studying IT value at this point of time.

The data set comprises firm-level data on 376 firms over the time span of 1988 through 1992, consisting of 1,115 observations out of a total of 1,850 possible data points due to missing values of some variables. Several inputs are measured in 1990 dollars: Non-Computer Capital (K), Non-IS Labor (L), Computer Capital, and IS Labor. The production factor for IT investments is calculated as IT stock (T) = Computer Capital + 3 × IS Labor (Dewan and Min 1997; Hitt and Brynjolfsson

1996). The multiplier of three in the calculation of T represents the assumed service life of the asset created by IS Labor. Such a multiplier has been used in previous work to study the relative contributions of IT in various subsectors of the economy. Finally, the Output (Y) represents the firm's value added, also expressed in 1990 dollars. To rule out the impact of inflation, the appropriate price deflators have been used to convert the nominal values of inputs and output into 1990 dollars.

The issue to be addressed in this study is the relationship between IT investments and productive efficiency. We ask the following question (test the hypothesis): "Does the relative size of IT investments have a positive influence on productive efficiency?" The reason why we look at the *relative* size of IT investments, rather than the *absolute* size, is that the data set consists of a wide spectrum of samples ranging from very large firms with ample resources to relatively small firms with few resources. Large firms tend to have more financial resources to invest in IT and, at the same time, are possibly subject to different production technologies.

To smooth out the effect of firm size, the samples in the data set are re-ordered based on the ratio of T to (Total Capital + 3 × Total Labor). Because T is defined as (Computer Capital + 3 × IS Labor), this ratio indicates the relative level of IT spending in comparison to a similar composite indicator of total capital and total labor. The data set is then equally divided into three groups according to the level of IT investments: low, medium, and high. The low-level group of IT investments consists of observations 1 through 370, with the ratio ranging from 0.0010 to 0.0134 and an average of 0.0085. The medium-level group contains observations 371 through 740, with the ratio from 0.0135 to 0.0252 and an average of 0.0186. The high-level group consists of observations 741 through 1,115, with the ratio from 0.0253 to 0.3427 and an average of 0.0487. Finally, the three groups are separately estimated using the Cobb-Douglas stochastic frontier of equation (4), the Box-Cox stochastic frontier of equation (5), and the Box-Tidwell stochastic frontier of equation (7).

The technique to partition the sample observations into subgroups has been used previousy for studying IT substitution for other production factors (Dewan and Min 1997) and for investigating the ideal level of mainframes in total computer capital (Brynjolfsson and Hitt 1996).

ESTIMATION METHOD

In estimating the stochastic frontier models as specified earlier and then measuring the technical (in)efficiency u_{it}, the first step calls for obtaining the ordinary least squares (OLS) estimates that will be used as the starting values for the unknown coefficients of the stochastic production frontiers in the second step (Schmidt 1985). The OLS estimates also are used to obtain starting values for the variance parameters for the models.

In the second step, maximum likelihood estimation (MLE) is undertaken, using the OLS estimates as the initial values. But before the MLE begins, the skewness of the OLS residuals first needs to be checked. Waldman (1982) has shown that the maximum likelihood estimators for a stochastic frontier model is simply the OLS if the OLS residuals are positively skewed. Therefore, if the exception condition (positive skewness) prevails, estimation is halted at that point. Otherwise, the residual is computed by the formula $E[u_{it} \mid (v_{it}-u_{it})]$ according to Jondrow et al. (1982).

All the results that follow are obtained using the LIMDEP statistical package software, which is capable of carrying out the OLS, the MLE, and the Waldman test and, hence, obtaining the expected value of u_{it}, conditional on $\epsilon_{it} = v_{it} - u_{it}$. Then, productive efficiency is measured by $e^{-u_{it}}$ (see Lovell 1993, p. 20).

IV. EMPIRICAL RESULTS

DISCUSSION AND FINDINGS

The estimation results for the Cobb-Douglas function are presented in Table 1. For the low IT level group, the average efficiency (AVG) is 0.792, the smallest among the three groups. The medium IT level group has an average efficiency of 0.898 and the high IT level group's average efficiency is 0.942. Such a finding on the relative size of IT investments and productive efficiency suggests that the firms spending comparatively more on IT are, on average, more productively or technically efficient in their production processes than those investing less on IT. The coefficient estimates of β_1, β_2, and β_3 for K, L, and T are all found significant at the .01 level.

Table 1. Estimation Results for the Cobb-Douglas Stochastic Frontier

IT Level \ Coefficient	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.237*	0.673*	0.064*	0.974	0.792	0.943
Medium (371-740)	0.129*	0.675*	0.180*	0.984	0.898	0.971
High (741-1115)	0.200*	0.710*	0.066*	0.976	0.942	0.981

(*significant at the .01 level)

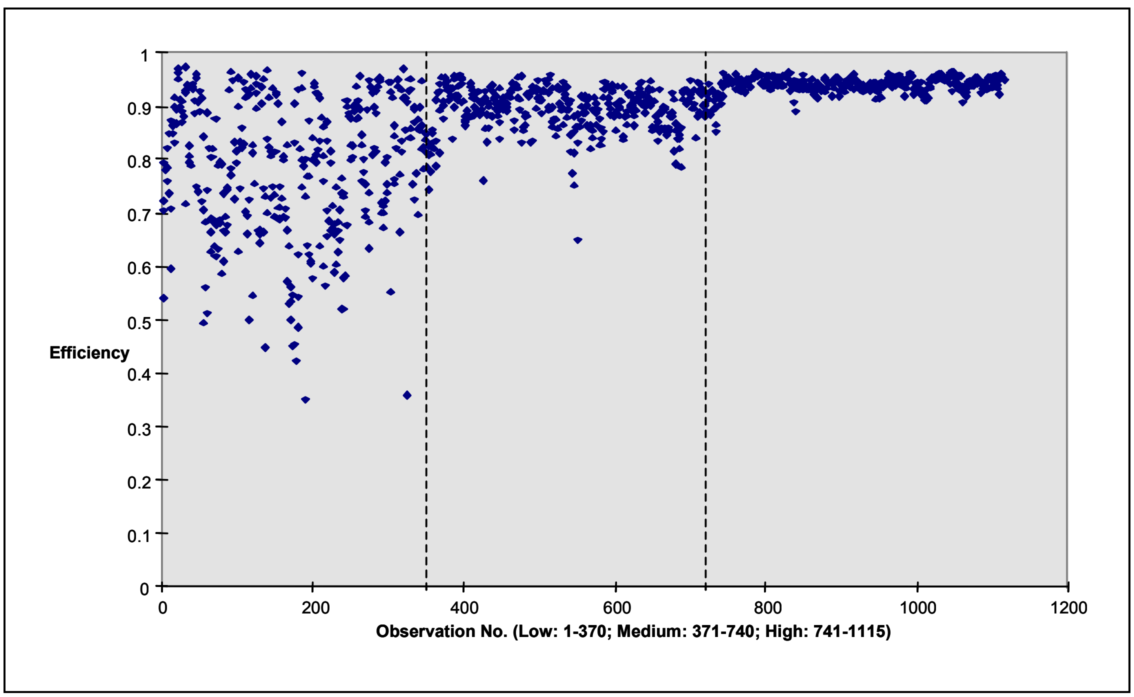

Figure 2. Efficiency Measures for the Cobb-Douglas Stochastic Frontier

The R^2 values increase with the level of IT investments and, hence, indicate that IT investments and other production factors in the high IT level group can better explain the output variability than in the medium and low IT level groups. The sums of coefficients in the three groups are all less than one, denoting a decreasing return to scale between inputs and output in the production process. Also, the different coefficients obtained for production factors across the three groups suggest that each group employs a particular production technology to produce output. The individual efficiency measures for the individual observations in the three groups are plotted consecutively in Figure 2.

Other estimation results are also obtained for the Box-Cox and Box-Tidwell transformations and are shown in Tables 2 and 3, respectively, along with their corresponding values for λ^*, δ^*, and L_{max}. On average, the high IT level group once again achieved the greatest measured efficiency, with the medium IT level group in between, and the low IT level group earning the smallest efficiency scores. In addition, the rankings of productive efficiencies and the R^2 values among groups are very similar across the different production frontiers assumed, thereby providing us with more convincing evidence of IT's positive impact on productive efficiency. Plotted efficiency measures also show similar scattered patterns across models, as illustrated in Figures 2, 3, and 4.

We have found evidence indicating that the relative size of IT investments has positive effects on organizational performance in terms of productive efficiency. For those firms investing relatively more in IT, their production processes are, on average, technically more efficient than those who spend less on IT. The empirical evidence implies that the gap between the actual and ideal output levels is narrowed in the presence of more IT investments. In other words, IT spending has been justified in terms of this efficiency measure of organizational performance.

Our findings on productive efficiency improvement by IT can be associated with previous research conducted on the same data set to explain, to some degree, productivity enhancement by IT as suggested in Hitt and Brynjolfsson's (1996) study. As stated earlier, productivity growth actually reflects the net effect of technical change and efficiency enhancement (Grosskopf 1993); Caves and Barton (1990), Lin and Chen (1999), and Fecher and Perelman (1992) have found that productive efficiency has a positive effect on productivity growth. In view of the findings of these studies, and since IT is found in our study to favorably influence the efficiency component of productivity growth, our conclusion serves as one source of, and a good explanation for, the disappearance of the IT productivity paradox, as claimed by Hitt and Brynjolfsson.

Table 2. Estimation Results for the Box-Cox Stochastic Frontier

IT Level \ Coefficient	β_1	β_2	β_3	AVG	R^2	λ^*	L_{max}
Low (1-370)	0.208*	0.826*	0.083*	0.788	0.951	0.239	-154.89
Medium (371-740)	0.132*	0.700*	0.198*	0.892	0.972	0.057	-83.70
High (741-1115)	0.198*	0.758*	0.078*	0.939	0.982	0.126	11.74

(*significant at the .01 level)

Table 3. Estimation Results for the Box-Tidwell Stochastic Frontier

IT Level \ Coefficient	β_1	β_2	β_3	AVG	R^2	λ^*	δ^*	L_{max}
Low (1-370)	0.190*	0.793*	0.053*	0.805	0.952	0.210	0.290	-149.23
Medium (371-740)	0.139*	0.701*	0.162*	0.892	0.973	0.036	0.078	-77.72
High (741-1115)	0.197*	0.759*	0.076*	0.933	0.983	0.127	0.134	12.23

(*significant at the .01 level)

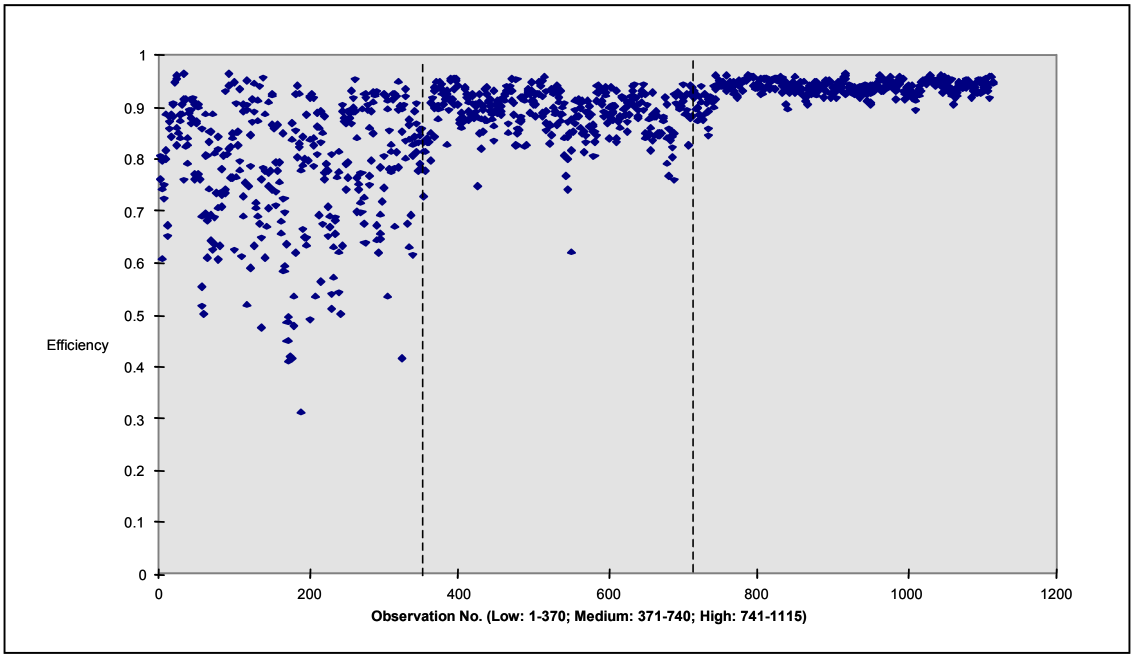

Figure 3. Efficiency Measures for the Box-Cox Stochastic Frontier

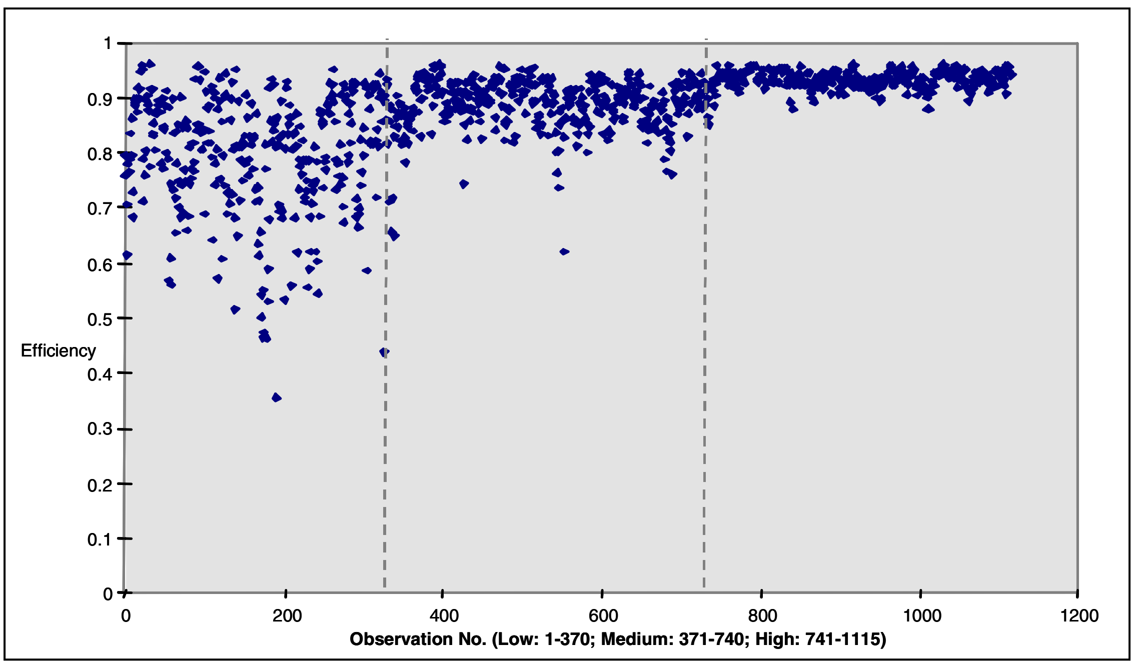

Figure 4. Efficiency Measures for the Box-Tidwell Stochastic Frontier

What can management learn from the findings reported in this study? First, when IT is treated as a production factor, efficiency of an "average" firm can be enhanced in its production process. Such a result is obtained after smoothing out the firm size effect. In other words, when IT is employed relatively more (compared to other production factors such as capital and labor), the actual output tends to be closer to the production frontier, leading to a smaller inefficiency gap. IT, therefore, helps approach the maximum possible production, confined by the production technology and described by the corresponding production function. As a result, we can justify IT spending for this particular organizational performance measure called productive (technical) efficiency.

Second, after recognizing that the relatively higher IT spending firm is more likely to be technically efficient in the production process, management may consider purchasing computer hardware en masse and training users more intensively in order to realize the potential efficiency benefit promised by IT. On the other hand, it should also be noted that effective IT management after installation is as important as the purchase. IT investments have been regarded as more venturesome than capital or human resource investments. As such, managers have to make sure that a sound IT management plan is in place to measure and monitor the IT benefits after the large initial expenditure.

Finally, along with the recent report that IT has a favorable impact on process output and quality (Mukhopadhyay et al. 1997b), managers are advised to apply IT to integrate all of the processes of design, production, quality control, delivery, and service after sales in a systematic manner so as to achieve synergy in reengineering processes with better quality, more diverse variety, higher efficiency, and greater productivity.

FACTOR SHARES AND ELASTICITY MEASURES: FURTHER DISCUSSION

The generalized Cobb-Douglas production function (3) is a widely used tool of research. This is simply because it is easy to apply, it has special properties (e.g., it is homogeneous of degree $\beta_1 + \beta_2 + \beta_3 > = < 1$), and the powers of its production factors have special meanings. Thus, it is instructive and worthwhile to explain the results in Table 1 in terms of factor shares and elasticity measures. Define e_{YK}, e_{YL}, and e_{YT} as the (partial) elasticity of output (Y) with respect to capital (K), labor (L), and IT stock (T), respectively. Further define S_K, S_L, and S_T as the factor share of K, L, and T, respectively. Then, it can be shown that under the marginal productivity pricing assumption,

$$S_K = e_{YK} = \beta_1,\ S_L = e_{YL} = \beta_2, \text{ and } S_T = e_{YT} = \beta_3.$$

Thus, $e_{YK} + e_{YL} + e_{YT} > = < 1$; and e_{YK}, e_{YL}, and e_{YT} also represent the (relative) shares of K, L, and T, respectively, out of total output (income). When $e_{YK} + e_{YL} + e_{YT} = 1$, i.e., when production factors are rewarded according to their marginal productivities, there is no summation problem. When $e_{YK} + e_{YL} + e_{YT} < 1$, part of the output is not paid to the factors of production, while when $e_{YK} + e_{YL} + e_{YT} > 1$, the total factor payments are more than the output. In other words, when the sum of factor shares is not equal to 1, there is a summation problem.

The summation problem implies that production factors get either less than or more than total output. If factors get less than total output, who gets the remainder? If factors get more than total output, from where do they get it? Neoclassic economic theory is unable to answer these questions. This is probably one of the reasons economists tend to assume constant returns to scale ($\beta_1 + \beta_2 + \beta_3 = 1$ or homogeneous of degree one), although in reality this is not a valid assumption.

Using these economic concepts regarding factor shares and output elasticities, we are able to explain the results reported in Table 1 one step further. First, since at all three levels the sum of the coefficients is less than 1 (0.974, 0.984, and 0.976 at the low, medium, and high levels, respectively), the production process is homogeneous of degree less than 1 (decreasing returns to scale) and a small portion (2.6%, 1.6%, and 2.4% at the low, medium, and high levels, respectively) of the product is not paid to the factors), but the production process is very close to homogeneity of degree 1.

Second, according to the estimated results, the labor factor gets the highest share (67.3%, 67.5%, and 71.0%) and the IT stock factor gets the lowest share (6.4%, 18%, and 6.6%) at all three levels. The share earned by the capital factor ranges from 12.9% at the medium level to 23.7% at the low level. These results are at variance with the traditional economic wisdom: the share of output that is paid to capital is much larger than the share that goes to labor.

Third, based on the theoretical concepts we just reviewed, the elasticity of output with respect to labor exhibits the highest value in comparison with the elasticities of output with respect to capital and IT stock. It is of particular interest to point out that the output is least elastic with respect to IT stock, meaning that output is much less responsive to IT stock than to capital and labor. Thus, the empirical evidence raises an important question, namely, how to increase the elasticity of output with respect to IT stock.

Nevertheless, since the estimates of β_3 are statistically highly significant (at the 1% level), we view the empirical evidence as strong support for the hypothesis that the effect of the relative level of IT investments upon the firm's productive efficiency is positive. This is true regardless of the magnitude of the estimated coefficients as measured by the factor share or of the output elasticity which directly affects the calculated productive efficiency of $e^{-u_{it}}$. It is evident that the employment of IT stock changes the factor shares of capital and labor as well as the output elasticities with respect to capital and labor.

SENSITIVITY ANALYSIS OF THE IS LABOR PARAMETER

The production factor of IT stock (denoted by T) consists of two components: computer capital and IS labor. That is, IT stock is defined as computer capital plus three times IS labor. Here, the IS labor parameter refers to the multiplier of three associated with IS labor in the formula. According to Hitt and Brynjolfsson, the three-year assumption seems to make sense because the components of IS labor spanned a range of activities such as software development, software maintenance and enhancement, user support, and hardware installation that ranged in useful life from less than a year to the life of a system.

Hitt and Brynjolfsson have also reported that the coefficients of the three input variables did not vary much as the multiplier (average service life) was changed over the range of one to seven years. Due to the fact that the same data set and the Cobb-Douglas production model are used, we expect that a similar argument can be made in our study.

As a result, it is instructive to conduct a sensitivity analysis on the parameter of IS labor by varying the average service life from one to seven years using the Cobb-Douglas model. The results are reported in Tables 4 through 9 for the multiplier equal to 1, 2, 4, 5, 6, and 7; the results for the multiplier equal to 3 have already been reported in Table 1. Based on the results, we are in a good position to corroborate the assertion that, in general, the coefficients of IT stock at the three levels (low, medium, and high) are fairly robust with respect to the changes in the multiplier, especially when the multiplier is greater than or equal to 2. For example, over the range of one to seven for the average service life, the coefficient of IT stock (β_3) at the low level is 0.038, 0.050, 0.064, 0.056, 0.064, 0.068, and 0.066, respectively. In other words, the sensitivity analysis for IS labor seems to reveal that the multiplier (or average service life) has an effect on the estimation of the coefficient of IT stock but is of small magnitude in many cases, meaning that there is some degree of sensitivity in the reaction of the coefficient of the IT stock factor to the changes in the multiplier.

A review of the response of the average efficiency (denoted by AVG) to a shift in the multiplier indicates that, at the low IT level, AVG tends to increase as the multiplier increases; on the contrary, at the high level, AVG tends to decrease as the multiplier increases; and at the medium level, AVG seems to display a fluctuating pattern.

Table 4. Multiplier Equal to 1 for the Cobb-Douglas Stochastic Frontier

Coefficient / IT Level	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.263*	0.688*	0.038*	0.989	0.785	0.944
Medium (371-740)	0.124*	0.789*	0.160*	0.993	0.909	0.975
High (741-1115)			w.s.*			

(*significant at the .01 level and w.s. = wrong skewness)

Table 5. Multiplier Equal to 2 for the Cobb-Douglas Stochastic Frontier

Coefficient / IT Level	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.252*	0.680*	0.050*	0.982	0.787	0.941
Medium (371-740)	0.112*	0.691*	0.181*	0.984	0.942	0.974
High (741-1115)			w.s.*			

(*significant at the .01 level and w.s. = wrong skewness)

Table 6. Multiplier Equal to 4 for the Cobb-Douglas Stochastic Frontier

Coefficient / IT Level	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.241*	0.677*	0.056*	0.974	0.797	0.944
Medium (371-740)	0.174*	0.663*	0.168*	1.005	0.902	0.966
High (741-1115)	0.202*	0.705*	0.071*	0.978	0.927	0.982

(*significant at the .01 level)

Table 7. Multiplier Equal to 5 for the Cobb-Douglas Stochastic Frontier

Coefficient / IT Level	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.236*	0.670*	0.064*	0.970	0.807	0.949
Medium (371-740)	0.123*	0.630*	0.299*	0.982	0.876	0.963
High (741-1115)	0.199*	0.696*	0.083*	0.978	0.919	0.982

(*significant at the .01 level)

Table 8. Multiplier Equal to 6 for the Cobb-Douglas Stochastic Frontier

IT Level \ Coefficient	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.233*	0.670*	0.068*	0.971	0.819	0.954
Medium (371-740)	0.127*	0.630*	0.224*	0.981	0.873	0.960
High (741-1115)	0.208*	0.681*	0.087*	0.976	0.884	0.981

(*significant at the .01 level)

Table 9. Multiplier Equal to 7 for the Cobb-Douglas Frontier

IT Level \ Coefficient	β_1	β_2	β_3	Sum	AVG	R^2
Low (1-370)	0.234*	0.668*	0.066*	0.968	0.818	0.953
Medium (371-740)	0.134*	0.613*	0.228*	0.975	0.863	0.959
High (741-1115)	0.212*	0.675*	0.090*	0.977	0.892	0.982

(*significant at the .01 level)

V. CONCLUDING REMARKS AND FUTURE RESEARCH

The ever-growing IT investments need to be justified not only academically but also practically. In previous research, a number of economic and financial measures have been used to evaluate the business benefits of IT. By inspecting productive efficiency, a topic rarely studied in the literature on IT value, this paper distinguishes itself from previous research on productivity. We examined the linkage between IT spending and efficiency and found empirical evidence to corroborate the contribution of IT investments in terms of this productive efficiency measure. The key result is both robust and consistent, regardless of the production frontier models (Cobb-Douglas, Box-Cox, and Box-Tidwell) assumed for the production technologies. Moreover, based on the relationship between productivity and efficiency, this paper provides one explanation to elucidate the disappearance of the

IT productivity paradox: the enhancement of the efficiency component in the productivity growth formula.

While this research contributes to the IT literature both in methodology and practice, it has some apparent limitations related to both data and methodology.

Since the firm-level data set used covers a short time series of only five years, it prevents us from formally considering time-lagged effects of IT (Brynjolfsson and Hitt 1996). Although time lags have been addressed somewhat through the three-year average life assumption for the IT stock created by IS labor, the three-year figure is still approximate (Hitt and Brynjolfsson 1996). Also, since the data set is becoming old, there is concern with the recency of the data (or the lack of up-to-date data). Although it is clearly beneficial to use the same data set as employed in previous studies, the data used are seven years old and quite momentous changes have been taking place in IT during this seven-year period. Therefore, a set of larger and more recent panel data is needed to undertake a current investigation of productive efficiency, including an analysis of the effect of time lags on productive efficiency as well as cross-sectional comparisons. Information on IS spending by U.S. firms is collected in a survey conducted annually by IDG. More recent data could be obtained if IDG were willing to release the survey data. The IS spending information from IDG then could be matched to Standard & Poors' Compustat II to obtain data on capital, labor, output, etc. (The authors requested the information from IDG but, unfortunately, the request was not fulfilled.)

We speculate that such momentous changes would have impacts on the two components (computer capital and IS labor) used to calculate IT stock (T), non-computer capital (K), and non-IS labor (L). The changes in the data on the production factors (K, L, and T) entering into a production function would result in changes in the estimates of the coefficients (e.g., β in the Cobb-Douglas stochastic frontier) and productive efficiency $(e^{-u_{it}})$.

Furthermore, we also speculate that the momentous changes in IT in the past seven years will have effects on the variables (t and $\mathbf{z}_{it}$) in the g function and firm sizes (which may be treated as a component of $\mathbf{z}_{it}$) when the generalized stochastic frontier model, represented by equations (a) and (b) in footnote 2 and proposed by Lin and Chen (1999), is pursued. Again, the changes in firm sizes and the measures of t and $\mathbf{z}_{it}$ would lead to differing estimates of β' and α and, hence, $e^{-u_{it}}$. In this situation, we speculate that the single equation model (2) would be insufficient and the generalized frontier model would better serve our purpose.

We speculate, however, that despite the changes in the magnitudes of the coefficients and productive efficiency estimates, our hypothesis that the relative size of IT investments has a positive influence on productive efficiency will still be supported by the data and our primary conclusion that the firm becomes more productively (technically) efficient when the IT investment is greater remains unchanged.

With respect to the limitations on methodology, we first recognize that the production models of Cobb-Douglas, Box-Cox, and Box-Tidwell consider only three kinds of production factors and may over-simplify the production processes (Dewan and Min 1997). The three input variables (K, L, T) for our study, however, can explain over 95% of the total variation in the output variable. The explanatory power of these three production factors is robust across different models. Nevertheless, inclusion of other input variables such as the type of IT, pollution prevention spending, manufacturing processes, and managerial strategies may further improve the predictive power of the models (Barua et al. 1995).

Another limitation relative to methodolgy is the econometric (model) specification. The stochastic frontier used in the present study is specified by equation (2). Virtually all previous research in the productive efficiency literature has been conducted under this single-equation frontier specification (e.g., Jondrow et al. 1982; Lovell 1993; Schmidt 1985). Recognizing that it is likely that u is dependent on various determinants, Lin and Chen (1999) have proposed a simultaneous equations system as formulated by equations (a) and (b) in footnote 2. The application of this system would reduce the potential for specification error in general, and simultaneity bias in particular, as shown by Lin and Chen. This will be an important area for future research.

The limitations on data and methodology call for future research. There are several avenues that can be pursued to extend the IT value research related to productive efficiency. First, the nonparametric approach of data envelopment analysis (DEA) used in the Banker et al. (1990) study may be applied to the same data set to compare the results and see if similar conclusions can be reached on the IT efficiency impact. Parametric and nonparametric approaches each have their own merits and limitations. The two approaches apply different techniques to envelop data more or less tightly in different ways. In so doing, they make different accommodations for random noise and for flexibility in the structure of production technology. Lovell (1993) claimed that neither approach strictly dominates the other. Based on these arguments, it is desirable to apply DEA to measure productive efficiency and compare the findings.

Second, another interesting direction for future research requires us to look at a different kind of economic efficiency—allocative efficiency (Banker and Maindratta 1988)—which indicates a particular combination of production factors among all the points on the production frontier to achieve the minimum cost. It suggests how IT influences the way the firm should allocate its resources in the production of products. To measure allocative efficiency, the data on the prices of inputs and output are needed. Productive (technical) efficiency is a necessary but not sufficient condition for allocative efficiency. Similarly, allocative efficiency is necessary but not sufficient for cost minimization. Therefore, the study of allocative efficiency may establish a link between the economic and financial aspects of IT value research.

Treating organization size as a variable, along with the partitioning scheme, is the third direction in exploring efficiency gains from the relative sizes of IT investments. This can be done by including organization size as a component of $\mathbf{z}_{it}$ in the Lin and Chen generalized stochastic frontier model. In investigating the benefits of productive efficiency, the data partitioning scheme and direct treatment of firm size as a variable influencing u_{it} can be used jointly; they do not conflict but rather reinforce each other.

A fourth direction for future research may follow the generalized frontier model proposed and tested by Lin and Chen. The model addresses the important issue of how productive efficiency is affected by certain macroeconomic and microeconomic factors and thus enables us to identify the sources of (in)efficiency. A re-examination based on the generalized frontier model is necessary since the dependence of productive efficiency u_{it} on other favorable and unfavorable events is not explicitly specified in the present study. These variables are not production factors per se and do not enter the production function directly. Such an in-depth study would make possible a comparison of the efficiency scores obtained from different frontier models. The follow-up research intends to extend, not to replace, the work undertaken in the present study.

Last but not the least, the generalized stochastic frontier model of Lin and Chen may be restructured as an identifiable simultaneous equations system to examine the possible interrelationships between Y and u. This essentially is an extension to the fourth direction above.

The first four extensions can be dealt with just like the single equation model (2); there is no estimation problem involved. However, there appears to be difficulty in estimating the last extension involving a simultaneous equations model. The traditional methods of estimation (e.g., the two-stage and three-stage least squares) fail because of the requirement that u itself or the random error (h) associated with u be a one-sided distribution (e.g., half-normal).

To sum up, this paper reflects one facet, but an important one, of IT business value in terms of productive efficiency. Using stochastic frontiers applied to a comprehensive firm-level data set, this study (1) confirms the positive effect of IT on the firm's productive efficiency in the production process; (2) provides a source to explain the disappearance of the productivity paradox; (3) suggests a direction for future research that may integrate both economic and financial aspects of previous research on IT benefits (gains); and (4) implies other directions for further research.

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