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Ownership, size, and efficiency: evidence from software companies in India

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Abstract

Purpose – The purpose of this paper is to discuss the trends in relative efficiency of software companies in India during 1999-2008 by applying input-oriented data envelopment analysis (DEA) model. Based upon the PROWESS Database of Centre for Monitoring Indian Economy (CMIE), the efficiencies were estimated for the Indian, multinational and group companies. Also, relationship between efficiency and size is examined.

Design/methodology/approach – The study applied DEA to measure relative efficiencies of software companies and two different DEA models, CCR and BCC, were applied to evaluate the relative efficiency of the sample software companies in India. Comparisons of efficiency scores based on ownership were carried out by applying ANOVA and *t*-statistics.

Findings – The mean overall technical efficiency (OTE) of the software industry in India during 1999-2008 was low at 0.477. The mean pure technical efficiency for the industry for the study period was found to be 0.654 suggesting that software firms, on an average, were wasting 35 per cent of their inputs. It was observed that the Indian-owned companies have relatively high OTE score as compared to foreign owned and group owned companies. The mean OTE score of PI companies was found to be greater than the other two categories. In terms of, size it is observed that medium sized companies performance better.

Practical implications – Software companies can use DEA to examine their performance against the best performers in the industry. Software industry in India, which is doted by large number of small firms in the lower part of the size pyramid, needs to increase their size to improve their efficiency.

Originality/value – Research on measurement of service sector export oriented industry efficiency is limited. This paper is one of the few published studies examined service sector performance. This paper fills the gap in the literature by applying DEA in software industry in India and compares performance in terms of ownership and size.

Keywords Performance measurement, Efficiency, Data envelopment analysis, Size, Ownership, Software industry in India

Paper type Research paper

1. Introduction

India's competitive advantage in producing software at lower cost is the driving force for remarkable success of the industry. However, mere presence of demand and competitive advantage may not be sufficient condition for the sector to grow as rapidly as it had in the last three decades. Producing efficiently is a critical factor that enables to catch on the existing world demand. Given the fact that software sector is one of the driving forces of service sector led growth story of India, and rising competition from other countries it is critical for India to maintain and improve the performance of this sector in future. Further, rising difficulty in sustaining the competitive advantage India has gained from its low-cost skilled labour it is important to improve efficiency of the industry,

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so that maximum, can be achieved from the skilled manpower that India has. In this context, it is pertinent to examine the current levels of efficiency in the industry with respect to size and ownership. Hence, the present study is a modest endeavour to estimates efficiency (overall efficiency, pure technical efficiency (PTE) and scale efficiency (SE)) of 72 software companies in India during 1999-2008, by applying two Data Envelopment Analysis (DEA) models namely, CCR (Charnes *et al.*, 1978), and BBC (Banker *et al.*, 1984). The efficiencies, then, are grouped into ownership, and size of companies.

The remaining of the paper is divided into four sections; the following section provides the methodology applied and presents the variables used in the analysis for computing efficiency. Section 3 reports the results pertaining to efficiency estimates, where efficiencies were grouped by ownership and size of the companies. Section 4 reports the concluding observations.

2. Methodology

The purpose of DEA is to construct a non-parametric piecewise frontier over the data set in such a way that all observed points lie either on or below the production frontier as it enables to calculate the relative efficiencies of all DMUs with respect to the frontier. Each DMU, not positioned on the frontier, is scaled down against a convex combination of DMUs on the frontier facet closest to it (Charnes *et al.*, 1978). CCR model proposed by Charnes *et al.* (1978), had an input-orientation and assumed constant returns to scale (CRS). Similarly, Banker *et al.* (1984) proposed BCC model which had assumed variable returns to scale (VRS). In an input-oriented technical efficiency (TE) measurement, output(s) remain constant but inputs are proportionally reduced. Similarly, keeping inputs unchanged, outputs can be expanded proportionally. The latter is called output-oriented measure of TE. Given the assumptions of constant and VRS, and two measures of TE (input or output orientation measure), it is critical to understand which should be the most appropriate tool for the study which is further discussed in the sub-section below.

2.1 Choice of DEA model

There are various DEA models as is amply demonstrated by the existing body of literature on DEA (Nigam *et al.*, 2012; Lau, 2012; Sreekumar and Mahapatra, 2011; Debnath and Shankar, 2008; Cooper *et al.*, 2007). In an input-orientation model (input minimization) desired output is produced with minimum inputs. This model is preferred when output is given and inputs are flexible. On the other hand, in an output orientation model (output maximization) efforts are made to maximize the output with given inputs. The choice of the model depends on the available flexibility either with the inputs or output (Avkiran, 2001).

The input variables taken for this study comprise employment, expenditure on hardware (computers and electronics equipments), operating expenditure and utility expenses. All these variables are considered to be flexible according to the requirements. Nevertheless, the output variable may not have flexibility as it is dependent on the exports, an overwhelming constituent of sales revenue. It may be appropriate to mention here that exports and even domestic sales are, by and large, governed by the orders received in advance. As a consequence, inputs appear to be more flexible than output in regard of the software industry. Hence, for the purpose of this study, input-oriented DEA model seems to be more appropriate than the output-oriented model.

Further in DEA analysis, making a choice between CRS and VRS is important. For instance, a CRS framework implicitly assumes that decision making units are operating in the optimum scales and there is no significant relation between scales of operations and efficiency. However, such presumptions may not always be tenable as different companies operate under different financial constraints and environment. On the other hand, VRS framework implies that a rise in inputs is expected to result in disproportionate rise in output. The VRS efficiency score represents TE, which measures inefficiencies arising out of inappropriate input/output configuration as well as size of the operations. CRS efficiency score, on the other hand, represents PTE which is a measure of efficiency without SE. It is, thus, possible to decompose TE into PTE and SE in a VRS framework. The present study attempts to estimate efficiency scores under VRS assumption as data set manifests large magnitude of differences which could be plausibly attributed to the existence of big and small companies in the sample (Cooper *et al.*, 2007).

2.2 DEA models

In order to describe DEA efficiency evaluation, first assume that there are n DMUs. The mth DMU use "I" inputs (x_i) and produce "j" outputs (y_j). The essential feature of the given ratio construction is the reduction of multiple-output and multiple-input into a single "virtual output" and "virtual input", respectively. Virtual output and virtual input is calculated by the weighed sum of all outputs and weighted sum of all inputs, respectively. Mathematically:

$$\text{Virtual input} = \sum_{i=1}^{I} u_i x_i;\ \text{Virtual output} = \sum_{j=1}^{J} v_j y_j \tag{1}$$

where u_i and v_j are weights for inputs and outputs, respectively. After these weights are picked for "mth" DMU, these weights are applied to the rest of the DMUs so that the ratio of "virtual output" to "virtual input" for the mth DMU is the highest. Further, no DMU is allowed to take weight as zero to avoid weak efficiency. Weak efficiency occurs when two DMUs have same score by choosing zero weights for inputs or/and outputs. Charnes *et al.* (1978) addressed the problem of weak efficiency by restricting the weights to be strictly positive. Another assumption in that no DMU transforms nothing into something. Average Productivity of mth DMU is:

$$AP_m = \frac{\sum_{j=1}^{J} v_j y_j}{\sum_{i=1}^{I} u_i x} \tag{2}$$

To find the weights we have to solve the following maximization problem:

$$\text{Max}\, E_m = \frac{\sum_{j=1}^{J} v_{jm} y_{jm}}{\sum_{i=1}^{I} u_{mi} x_{im}} \tag{3}$$

Subject to:

(1) none of the weights are negative; and

(2) evaluated at these weights, efficiency of none of the firms exceed more than one:

Thus two constrains are: v_j and $u_j \geqslant 0$, and $\sum_{j=1}^{J} v_{jm} y_{jn} / \sum_{i=1}^{I} u_{mi} x_{in} \leqslant 1$.

Now constrain two can be written as: $\sum_{j=1}^{J} v_{jm}y_{jn} \leqslant \sum_{i=1}^{I} u_{mi}x_{in}$.

These are linear constrains, but the objective function is not linear. Therefore putting another constrain will make the objective function linear, and it is given by: $\sum_{i=1}^{I} u_{mi}x_{im} = 1$.

Now the optimization problem is:

$$\left.\begin{array}{l} \mathrm{Max}\, E_m \sum_{j=1}^{J} v_{jm}y_{jm} \text{ Subject to:} \\ \sum_{i=1}^{I} u_{mi}x_{im} = 1 \\ \sum_{j=1}^{J} v_{jm}y_{jn} \leqslant \sum_{i=1}^{I} u_{mi}x_{in} \end{array}\right\} \quad (4)$$

$$v_j \geqslant \varepsilon \text{ and } u_i \geqslant \varepsilon$$

where E_m is efficiency of mth DMU. y_{jm} is amount of jth output produced by mth DMU; x_{im} is the amount of ith input used by mth DMU; "n" is number of DMUs, "j" number of outputs, "I" number of inputs. ε is a positive constant, i.e. non-Archimedean constant.

This optimization problem is known as the CCR multiplier model. This is interpreted that the objective is to maximize virtual output subject to unit virtual input while maintaining the condition that virtual output cannot exceed virtual input for any DMU. If the optimal value of the objective function is one and all weights are strictly positive, then $\mathrm{DMU_m}$ is fully efficient. If the value is less than one it is weak efficient. In the CCR model CRS was assumed. The dual of the optimization problem is given by:

$$\left.\begin{array}{l} \mathrm{Min}\, Z_m = \theta_m - \varepsilon \sum_{j=1}^{j} S_{jm}^{+} - \varepsilon \sum_{i=1}^{i} S_{im}^{-} \text{ Subject to:} \\ \sum_{m=1}^{n} \lambda_{jm}y_{jm} - S_{jm}^{+} = y_{jm} \text{ for all } j = 1,\ 2\ldots, j \\ \sum_{m=1}^{n} \lambda_{jm}x_{im} + S_{im}^{-} = \theta_m x_{im} \text{ for all } i = 1,\ 2, \ldots, i \end{array}\right\} \quad (5)$$

$$\lambda_{jm} \geqslant 0 \text{ for all } m = 1,\ 2\ldots n$$

$$\theta_m \text{ is unrestricted in sign, and } S_{jm}^{+} \geqslant 0,\ S_{im}^{-} \geqslant 0$$

where S_{jm}^{+} = slack in jth output of mth DMUS_{im}^{-} = slack in ith input of mth DMU λ_{jm} = dual variables known as intensity variables.

θ_m is the scalar reduction allied all inputs of $\mathrm{DMU_m}$ to improve its efficiency. The reduction is applied simultaneously to all inputs and results in a radial movement towards the envelopment surface. This is popularly known as CCR Envelopment Model.

Interpretations of results are as: The DMU_m is Pareto efficient if $\theta_m = 1$ and all slacks are zero. A DMU is weakly efficient if $\theta_m = 1$ but at least one slack is non-zero.

Another model of DEA is BCC model developed by Banker *et al.* (1984). In the BCC model VRS is assumed in place of CRS. The basic difference between BCC model and CCR model is the convexity constraint, which represents different returns to scale. In the BCC model $\sum_{j=1}^{j} \lambda_{jm} = 1$ assumed in place of $\lambda_{jm} \geqslant 0$. The BCC model estimates only PTE, whereas CCR model estimates overall technical efficiency (OTE). The ratio of OTE to PTE measures the SE. The multiplier and envelopment BCC models are presented below:

$$\left.\begin{aligned}
&\operatorname{Max} E_m \sum_{j=1}^{J} v_{jm} y_{jm} + \mu_{0m} \text{ Subject to:}\\
&\sum_{i=1}^{I} u_{mi} x_{im} = 1\\
&\sum_{j=1}^{J} v_{jm} y_{jn} - \sum_{i=1}^{I} u_{mi} x_{in} + \mu_{0m} \leqslant 0
\end{aligned}\right\} \quad (6)$$

$$v_j \geqslant \varepsilon \text{ and } u_i \geqslant \varepsilon$$

μ_{0m} is unrestricted in sign If $\mu_{0m} <\ 0$ imply increasing returns to scale; $\mu_{0m} = 0$ imply CRS; $\mu_{0m} >$ imply decreasing returns to scale.

The envelopment version of BCC model is:

$$\left.\begin{aligned}
&\operatorname{Min} Z_m = \theta_m - \varepsilon \sum_{j=1}^{j} S_{jm}^{+} - \varepsilon \sum_{i=1}^{i} S_{im}^{-} \text{ Subject to:}\\
&\sum_{m=1}^{n} \lambda_{jm} y_{jm} - S_{jm}^{+} = y_{jm} \text{ for all } j = 1, 2 \ldots, j\\
&\sum_{m=1}^{n} \lambda_{jm} x_{im} + S_{im}^{-} = \theta_m x_{im} \text{ for all } i = 1, 2, \ldots, i
\end{aligned}\right\} \quad (7)$$

$$\sum_{j=1}^{j} \lambda_{jm} = 0 \text{ for all} = 1, 2, \ldots, n$$

θ_m is unrestricted in sign, and $S_{jm}^{+} \geqslant 0$, $S_{im}^{-} \geqslant 0$

2.3 Data sources and variable construct

Primary data source of the study is PROWESS compiled by Centre for Monitoring Indian Economy (CMIE). PROWESS compiles financial information of the companies out of their annual balance sheets. It provides data on sales (value of output), exports, wages and salaries, gross fixed assets, net fixed assets, total and net assets, capital expenditure and expenditure on computer/electronics installation in nominal terms. For computing efficiency, total sales are taken as output variables, and employment, expenditure on computers and electronics equipments, operating expenditure (includes expenditure on software, repairs and maintenance of machinery and building and training expenses, etc.), and power, fuel (including wheeling charges paid by electricity companies) and water charges as the input variables.

2.3.1 Output variable: sales revenue. In productivity analyses, gross value added is generally taken as the output variable. However, there are some empirical studies that have used gross value of output as the output variable (Chen and Ali, 2004). The use of gross value output is indeed a better measure than gross value added, especially in an industry, such as software, where intermediate inputs are insignificant. Specific studies related to software industries have also used sales and exports to measure the progress of the industry over the years. In case of India, a fair number of studies (NASSCOM, 2012; Arora *et al.*, 2010; Athreye, 2005; Heeks, 1996) have also made use of sales revenue and export revenue to examine the progress of Indian software industry. The sales revenue, therefore, has been taken as a measure of output for this study.

2.3.2 Input variables. 2.3.2.1 Employment. Labour is an important input for any production process, and in case of skill intensive industry, such as software industry, labour is the most significant input. In PROWESS database of CMIE, the data on number of employees have been reported. However, for many firms, it has been reported as zero despite positive sales and exports. Thus, this kind of employment data are not suitable for the purpose of this study. Nevertheless, PROWESS database also provides data on total wages and salaries which could be used for computing employment data. One method for doing so is to divide wages and salaries by the industry wage rate. This method has been used in a number of studies. However, such studies assume industry-wide equal wage rates, which does not appear to be realistic in the light of well-documented evidence of substantial inter-firm wage rate heterogeneity even among narrowly defined industries (Fairris, 2005). The prevalence of wage rate heterogeneity among firms in the software sector is further corroborated by the existence of very high attrition rate in this industry. Existing body of literature suggests that the number of employees is highly correlated to total assets of a given firm (White and Liu, 1998). The high degree of correlation between wages and salaries and total assets can very plausibly be explained by the fact that a firm high in total assets may employ more personnel than those lower in total assets. This variable, then, can be used for computing employment elasticity by running a regression of the log of wages and salaries on the log of total assets and time. The elasticity coefficient obtained from this regression then could be used for predicting employment data for a given firm. The same has been done in this case too. It may be mentioned here that the correlation between wages and salaries and the total assets of the firms, considered for this study, was found to be very high at 0.89.

The regression results provide high score of goodness of fit as F-value is found to be statistically significant. R^2 value is 0.775, implying that more than 77 per cent of variation in the dependent variable, i.e. log of wages and salary is explained by the independent variable, i.e. total assets. Elasticity of wages and salary with respect to total assets is found to be 0.956 for software services. This elasticity coefficient, then, was used for estimating employment data (Table I).

2.3.2.2 Expenses on computer and electronic instruments. In software industry, computers and electronics instruments are major part of the intermediate costs which are used for generating softwares. Therefore, expenditure on computer and electronic instruments has been taken as one of the inputs for computing productivity.

2.3.2.3 Operating expenditure. Another important input cost in the software industry is the operating expenses, which include expenditure on software, repairs and maintenance of machinery and building, and training of personnel etc. Therefore, for the present study, operating expenses is used as one of the input variable.

2.3.2.4 Utility expenditure. Utility expenses which include power, fuel and water charges also constitute an important part of intermediate inputs in the production process in the software industry. This variable has been taken as input variable for this study.

Since the PROWESS database provides data on current prices, they had to be converted to constant price series (1993-1994 constant prices) by applying Wholesale Price Index (WPI) as reported by Reserve Bank of India (RBI). Further, as WPI for service sector is not available; WPI for industrial worker was taken for converting sales revenue and operating expenditure to constant price series. Similarly, expenses on computer and electronic instruments were deflated by composite price index of computer and computer based systems, and electronic equipments. Utility expenses were deflated by composite price index of fuel and power. Different sets of WPI, as reported by RBI, were applied to convert the above variables to constant prices as per the classification of these specific variables.

3. Empirical results and interpretations

Mean OTE of the 72 software industry in India during 1999-2008 found to be 0.477, suggesting thereby, if inputs will reduced by about 52 per cent still then the output will remain same given inputs are most efficiently used. Low level of overall efficiency in the software industry is not surprising because general efficiency of service sector is lower than the manufacturing/commodity sector. But the compound annual growth rate of 1.8 per cent suggesting a declining trend of mean OTE for the industry during the study period is a matter of concern. It can be observed from Figure 1 that mean SE with a score of 0.757 of the industry is the highest compared to PTE and OTE. The mean PTE for the industry for the study period was found to be 0.654 suggesting that software firms, on an average, were wasting 35 per cent of their inputs. This suggested that overall software industry in India is operating at low efficiency level. Therefore, if it has to compete with the global player in future it needs to improve its efficiency.

	Coefficients	SE	*t*-stat.	*p*-value
Intercept	−1.682*	0.158	−10.633	0.000
Log of total assets	0.956*	0.035	27.575	0.000
Time	0.034**	0.020	1.670	0.095
R^2	0.775			
Adjusted R^2	0.765			
F-value	452.9*			0.000
D-W statistics	2.02			
Number of observation	648			

Note: *,**Significant at 1, 5, and 10 per cent, respectively

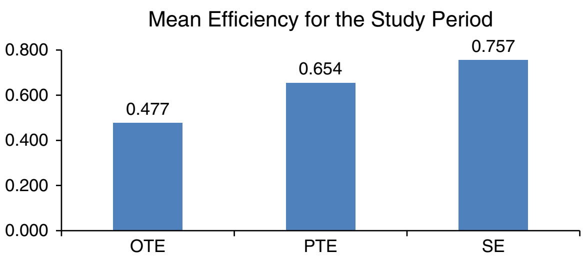
Table I. Elasticity of employment with respect to total assets

3.1 Company-wise average OTE, PTE and SE scores

Company-wise average OTE, PTE and SE scores are reported in Table II. The average OTE score for all the companies in the sample is estimated at 47.7 per cent, which suggested that, on an average, software industry can reduce its inputs by 53.3 per cent and still can maintain its present sales revenue, provided it can operate on the production frontier. The average sale revenue loss due to pure technical inefficiency was found to be 34.6 per cent and due to scale inefficiency 24.4. Thus, output of software industry can be pegged up by 24.4 per cent by increasing their scale of operation. Looking at the individual company's average score of different efficiency scores, it is found that Glodyne Technoserve Ltd has unity score in three dimensions of efficiency. This suggested that it has maintained its performance throughout the study period and has been constantly operating on MPSS.

Cybertech Systems, on the other hand, has recorded the lowest average OTE score, suggesting that it was the worst performing company during the study period. Its average OTE during the study period stood at 0.102, implying that it could reduce its inputs by 89.8 per cent and still maintain its total sales. Besides Glodyne Technoserve Ltd, there were four more companies, namely CMC Ltd, Infosys Technologies Ltd, Prithvi Information Solutions Ltd and Wipro Ltd which had unity mean PTE scores for the study period. The mean PTE score of Ramco Systems Ltd has registered the lowest score of efficacy (0.195). In terms of SE, Four Soft Ltd was found to be on the lowest ladder with the score of 0.179. It is also discernible from Table II that for 35 companies, mean SE score is greater than PTE scores suggesting that these companies were utilizing their size more effectively than converting the inputs to output. Now let us discuss the efficiency of software companies according to their ownership category.

3.1.1 Efficiency by ownership. Ownership is categorized as private Indian (PI), private foreign (PF) and group (G) owned companies (A group owned companies may be owned by a group only from India or from aboard or both). In the overall sample of 72 companies, 31, 21 and 20 are PI, PF and G owned companies, respectively. The mean SE scores for PI companies, as compared to their mean OTE and mean PTE scores, is observed to be higher throughout the study period. It can be further seen that the mean OTE and PTE scores of PI owned companies were moving in the same direction and followed same pattern indicating thereby that PTE exercised relatively stronger impact on OTE. In contrast to this, in regard of PF companies, SE seems to be exercising relatively higher impact on OTE as they appear to be moving in the same direction and followed same pattern. For the group owned companies, mean SE scores were higher than the mean OTE and PTE scores during the study period. Mean SE score for group owned companies registered continuous decline until



Source: Computed by author from CMIE, Prowess database

Figure 1.
Mean efficiency of sample companies for the study period

Firm	Mean OTE	Mean PTE	Mean SE	Rank OTE	Rank PTE	Rank SE
3I Infotech Ltd	0.194	0.205	0.948	68	67	4
Accel Frontline Ltd	0.605	0.700	0.864	14	21	21
Aftek Ltd	0.558	0.637	0.876	18	32	19
Aptech Ltd	0.515	0.608	0.846	27	35	26
Aurionpro Solutions Ltd	0.216	0.835	0.258	67	11	71
Aztecsoft Ltd	0.359	0.416	0.863	40	52	22
Birlasoft Ltd	0.566	0.632	0.896	16	33	15
Blue Star Infotech Ltd	0.469	0.532	0.880	30	44	18
Bristlecone India Ltd	0.586	0.679	0.863	15	24	23
CMC Ltd	0.871	1.000	0.871	3	1	20
California Software Co. Ltd	0.338	0.640	0.528	51	31	61
Compucom Software Ltd	0.353	0.698	0.506	42	22	63
Computech International Ltd	0.829	0.983	0.844	4	2	27
Cybertech Systems & Software Ltd	0.102	0.336	0.304	72	64	68
Datamatics Global Services Ltd	0.294	0.395	0.745	57	54	43
Datamatics Ltd (merged)	0.314	0.382	0.822	54	58	31
Flextronics Software Systems Ltd (merged)	0.558	0.669	0.834	17	26	28
Four Soft Ltd	0.172	0.960	0.179	69	4	72
Genesys International Corpn. Ltd	0.238	0.589	0.404	64	37	67
Geodesic Ltd	0.341	0.754	0.452	49	16	66
Geometric Ltd	0.277	0.295	0.940	58	65	6
Glodyne Technoserve Ltd	1.000	1.000	1.000	1	1	1
Goldstone Technologies Ltd	0.370	0.589	0.628	38	36	51
HCL Technologies Ltd	0.341	0.718	0.474	50	17	65
Hewlett-Packard Globalsoft Pvt. Ltd	0.538	0.702	0.767	23	19	38
Hexaware Technologies Ltd	0.386	0.411	0.938	37	53	8
Hinduja Ventures Ltd	0.147	0.244	0.602	71	66	55
ITC Infotech India Ltd	0.350	0.376	0.932	44	59	12
Igate Global Solutions Ltd	0.513	0.701	0.731	28	20	44
Infosys Technologies Ltd	0.804	1.000	0.804	5	1	36
Infotech Enterprises Ltd	0.351	0.384	0.915	43	57	13
KLG Systel Ltd	0.248	0.340	0.729	62	63	45
KPIT Cummins Infosystems Ltd	0.521	0.555	0.939	24	41	7
Kale Consultants Ltd	0.410	0.656	0.626	35	27	52
Larsen & Toubro Infotech Ltd	0.719	0.901	0.797	8	8	37
Mascon Global Ltd	0.440	0.538	0.818	33	43	33
Mastek Ltd	0.798	0.804	0.992	6	14	2
Megasoft Ltd	0.268	0.419	0.640	60	51	49
Melstar Information Technologies Ltd	0.342	0.645	0.531	48	30	60
Micro Technologies (India) Ltd	0.775	0.960	0.808	7	5	35
Mindteck (India) Ltd	0.228	0.812	0.280	65	13	69
Mphasis Ltd	0.348	0.425	0.819	45	50	32
NIIT Ltd	0.332	0.443	0.750	52	47	42
Nucleus Software Exports Ltd	0.299	0.366	0.817	56	60	34
Onward Technologies Ltd	0.239	0.361	0.662	63	62	47
Oracle Financial Services Software Ltd	0.345	0.621	0.556	47	34	58
PSI Data Systems Ltd	0.550	0.645	0.853	20	29	24
Panoramic Universal Ltd	0.266	0.951	0.280	61	6	70

(*continued*)

Table II. Average OTE, PTE and SE across companies

Firm	Mean OTE	Mean PTE	Mean SE	Rank OTE	Rank PTE	Rank SE
Polaris Software Lab Ltd	0.515	0.674	0.764	26	25	39
Prithvi Information Solutions Ltd	0.935	1.000	0.935	2	1	11
Quinnox Consultancy Services Ltd	0.637	0.845	0.755	11	10	41
Quintegra Solutions Ltd	0.354	0.653	0.542	41	28	59
R S Software (India) Ltd	0.663	0.708	0.936	10	18	10
R Systems International Ltd	0.273	0.431	0.634	59	49	50
Ramco Systems Ltd	0.161	0.195	0.827	70	68	29
Rolta India Ltd	0.331	0.435	0.762	53	48	40
SQL Star International Ltd	0.311	0.526	0.592	55	45	56
Sasken Communication Technologies Ltd	0.369	0.394	0.937	39	55	9
Satyam Computer Services Ltd	0.467	0.964	0.484	31	3	64
Sonata Software Ltd	0.347	0.385	0.900	46	56	14
Spanco Ltd	0.548	0.581	0.943	21	38	5
Subex Ltd	0.431	0.522	0.825	34	46	30
Syntel Ltd	0.400	0.554	0.722	36	42	46
Tata Elxsi Ltd	0.612	0.685	0.893	12	23	16
Tata Technologies Ltd	0.542	0.568	0.953	22	40	3
Tech Mahindra Ltd	0.608	0.925	0.657	13	7	48
Teledata Informatics Ltd	0.555	0.895	0.619	19	9	53
Tera Software Ltd	0.461	0.825	0.559	32	12	57
Wipro Ltd	0.520	1.000	0.520	25	1	62
Xansa (India) Ltd	0.510	0.580	0.880	29	39	17
Zensar Technologies Ltd	0.225	0.363	0.610	66	61	54
Zylog Systems Ltd	0.680	0.798	0.851	9	15	25

Note: 1999-2000 to 2007-2008
Source: Computed by author from CMIE, Prowess database

Table II.

2003-2004 when it registered an increase for two years before recording a wane. It can also be observed that PTE has relatively stronger impact on OTE for group owned companies (Table III).

It was observed that the PI companies have relatively high OTE score as compared to PF and group owned companies. For example, average OTE score for the study

	Mean OTE			Mean PTE			Mean SE		
Year	PI	PF	G	PI	PF	G	PI	PF	G
1999-2000	0.544	0.320	0.387	0.651	0.571	0.476	0.836	0.556	0.812
2000-2001	0.439	0.414	0.382	0.579	0.539	0.452	0.758	0.769	0.845
2001-2002	0.455	0.404	0.323	0.603	0.655	0.418	0.753	0.617	0.772
2002-2003	0.585	0.443	0.393	0.690	0.606	0.510	0.848	0.732	0.772
2003-2004	0.355	0.237	0.242	0.574	0.585	0.397	0.619	0.404	0.610
2004-2005	0.421	0.295	0.253	0.613	0.562	0.417	0.686	0.524	0.606
2005-2006	0.625	0.515	0.429	0.823	0.745	0.557	0.760	0.691	0.770
2006-2007	0.513	0.425	0.389	0.703	0.631	0.536	0.730	0.673	0.725
2007-2008	0.464	0.374	0.286	0.648	0.615	0.492	0.716	0.608	0.581
Mean	0.482	0.372	0.336	0.650	0.609	0.470	0.742	0.609	0.715

Source: Computed by author from CMIE, Prowess database

Table III.
Mean OTE, PTE and SE scores by ownership

period for all the PI companies stood at 0.482 whereas it was found to be 0.372 and 0.336 for PF owned companies and group owned companies, respectively. Mean OTE score for PI companies was found to be highest for all the years and lowest for group owned companies except for the year 1999-2000 when mean OTE score of PF companies was lowest. These scores highlighted that the inefficiency levels in the PI, PF and group owned companies were 51.8, 62.8 and 66.4 per cent, respectively, thereby suggesting that although the levels of inefficiencies are very high across all companies yet PI companies appeared to be performing better on efficiency fronts than the other two categories (Table III).

One plausible reason for the better efficiency of PI firms could be that while facing tough competition from the subsidiaries of multinational software companies in the labour market, and increasing competition from group owned companies in the software services and customized products markets, they preferred to invest to develop organizational capability by adapting business models of multinationals, in order to move to higher value-adding business models (Athreye, 2005). Further Indian affiliates of multinational software companies and group owned companies, unlike PI companies, are under no great competitive pressure as both these categories, by and large, feed to their parent concerns. Thus, improvement in organizational capabilities leading to more efficient use of existing human capital resources and greater competitive stress, arising out of the fact that exports form a major part of their sales revenue, could be one likely reason for the better efficiency of PI companies as compared to other two categories. Better organizational capability also comprises the skills of software managers to obtain export business including the negotiation of contracts, follow-up customer services, procurement of quality certification and seeking non-equity strategic alliances with the foreign firms. All of these are extremely important for the survival and growth in the export markets. It is observed that OTE scores for all the three categories of companies have recorded the same pattern. The mean OTE scores of all the three categories of companies reached at their respective minimum points in the year 2003-2004 and at peak in the year 2005-2006 (Table III).

The mean PTE scores of the PI and PF firms seems to be following same pattern as is displayed by mean OTE scores. Since, the mean PTE score of PI, PF and group owned companies were 0.650, 0.609 and 0.470, respectively; it appears to be suggesting that PI companies are relatively more efficient in converting inputs to output than PF and group owned companies. The highest PTE score was achieved by PI companies in the year 2005-2006. PF companies have followed the same pattern. PTE score of group owned companies remained low as compared to their counterparts during the period under reference (Table III).

Although, there does not appear to be any clear indication regarding which category of companies is performing better with respect to SE; however, it appears that PI and group owned companies have fared much better as compared to PF companies. Mean SE score of PI companies reached the maximum in the year 2002-2003 and slipped down to the minimum in the year 2003-2004. For the PF companies and the group owned companies, the highest SE score was found to be in the year 2000-2001 while the lowest score during 2003-2004 (Table III).

It is evident from Table III that, PI and PF companies have performed better in terms of PTE score whereas group owned companies appeared to be better in SE score. As a corollary to the above discussion, it can be suggested that the poor score of OTE of group owned companies emanate from their low PTE scores. However, it should also be noted that mean OTE scores for all the three category of companies were quite low in absolute terms which seems to indicate that software companies, across the board, are inefficient.

To examine the difference in the mean scores of efficiencies according to ownership categories, *F*-statistic (ANOVA) was applied. For this purpose, mean efficiency score for each company was computed over the study period then taking these mean efficiency scores *F*-statistics was estimated. The ANOVA results, as reported in Table IV, indicate that mean scores of efficiencies among the three categories of ownership exhibits statistically significant difference. *F*-statistics suggest that the mean OTE scores, for various ownership categories, demonstrate statistically significant difference. Same was found for PTE and SE.

In order to undertake pair-wise comparison in mean efficiency scores, *t*-statistics was calculated and reported in Table V. It can be observed that there is statistically significant difference in mean OTE scores between PI and PF companies; and PI and group owned companies. The mean OTE score of PI companies was found to be greater than the other two categories. In case of PTE, statistically significant difference was observed between PI and group owned companies; such a difference was not found between PI and PF companies. The difference in mean PTE between PF and group owned companies was found to be statistically significant and mean PTE of PF companies was found to be greater than the group owned companies, suggesting thereby that PF companies are doing better in converting inputs to outputs than group owned companies. The difference in mean SE between PI and PF companies observed to be statistically significant but in regard of PI and group owned companies, the case was not the same. On the other hand, the difference is found to be statistically significant between PF and group owned. From the preceding discussion, it is evident that PI companies are performing better than the other two categories of companies. The better performance of PI companies may be attributed to diasporic effect and in this category the owner his/her self as a workers, so puts more efforts to improve efficiency. Now let us discus efficiency of software industry with respect to company's size.

3.1.2 Size and efficiency. To examine the relationship between size and efficiency for each year, companies were arranged in ascending order of size (measured by total assets)

Table IV. Difference in mean efficiency scores according to ownership

	Sum of squares	df	Mean square	*F*	Sig.
Mean OTE					
Between groups	0.104	2	0.052	8.139*	0.002
Within groups	0.153	69	0.006		
Total	0.257	71			
Mean PTE					
Between groups	0.162	2	0.081	18.667*	0.000
Within groups	0.104	69	0.004		
Total	0.266	71			
Mean SE					
Between groups	0.081	2	0.040	6.417**	0.023
Within groups	0.219	69	0.009		
Total	0.299	71			

Notes: df, degrees of freedom. *,**Significant at the 0.01 and 0.05 level, respectively
Source: Computed by author from CMIE, Prowess database

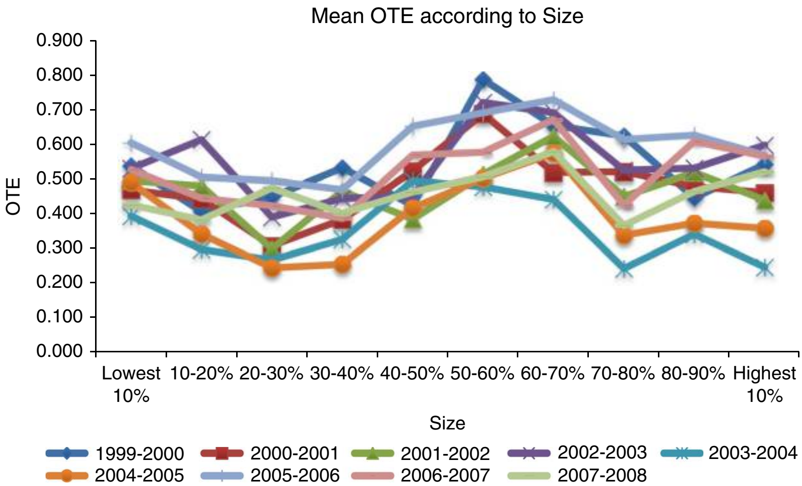
Dependent variable	Ownership		Mean difference	SE	Sig.
Mean OTE	Private Indian	Private foreign	0.108*	0.038	0.008
		Group owned	0.146*	0.038	0.001
	Private foreign	Private Indian	−0.108*	0.038	0.008
		Group owned	0.038	0.038	0.322
	Group owned	Private Indian	−0.146*	0.038	0.001
		Private foreign	−0.038	0.038	0.322
Mean PTE	Private Indian	Private foreign	0.042	0.031	0.191
		Group owned	0.181*	0.031	0.000
	Private foreign	Private Indian	−0.042	0.031	0.191
		Group owned	0.139*	0.031	0.000
	Group owned	Private Indian	−0.181*	0.031	0.000
		Private foreign	−0.139*	0.031	0.000
Mean SE	Private Indian	Private foreign	0.126*	0.045	0.010
		Group owned	0.024	0.045	0.603
	Private foreign	Private Indian	−0.126*	0.045	0.010
		Group owned	−0.102**	0.045	0.033
	Group owned	Private Indian	−0.024	0.045	0.603
		Private foreign	0.102**	0.045	0.033

Note: *,**Significant at the 1 and 5 per cent level, respectively
Source: Computed by author from CMIE, Prowess database

Table V. Pair-wise difference in mean efficiency scores according to ownership

and then the companies were classified into different decile groups like the lowest 10 per cent, next 10 per cent and so on up to highest 10 per cent. The mean OTE, PTE and SE were then computed for each decile group for each year and the results are presented in Figure 2.

It can be observed that the companies, in general, within the deciles groups 20-40 per cent have lowest mean OTE scores whereas for the decile groups ranging between 50-70 per cent have scored highest. It seems to suggest that medium size company's performance is better than other decile groups. However, in case of PTE, as



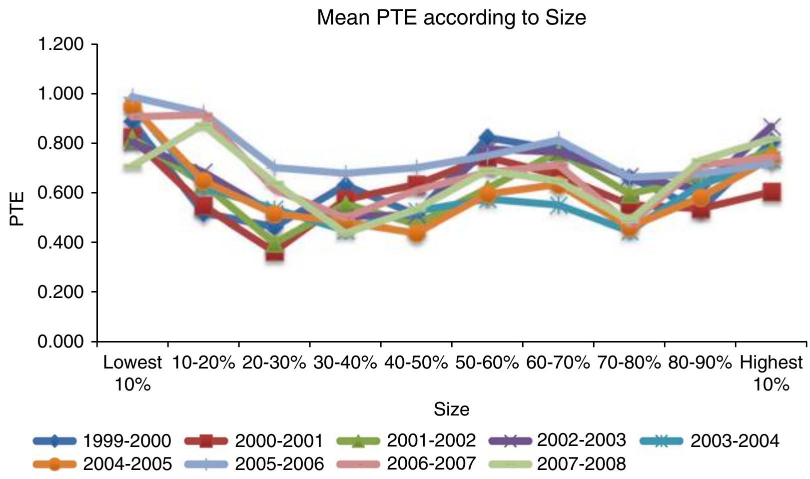
Source: Computed by author from CMIE, Prowess database

Figure 2. Mean OTE according to size

is evident from Figure 3, the lowest 10 per cent and highest 10 per cent deciles groups were found to be performing better than others, thereby, appear to be suggesting that small and large companies are more efficient that the medium size companies in converting inputs to output.

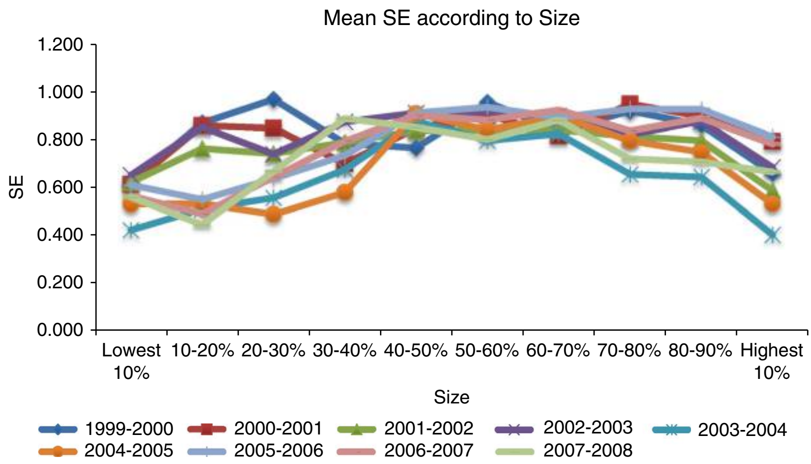
As can be evinced from Figure 4 in terms of mean SE, companies which are in the rage of 40-70 per cent deciles groups have highest score, whereas for the companies in the domain of lowest and highest deciles groups have lowest mean SE scores.

Thus it indicates that medium size companies are harnessing their size better than the small and large companies. This may be due to the possibility that whereas small size companies may have shortage of manpower to exploit the scale benefits, it could either be the disproportionate size as compared to the manpower base or inefficient manpower management in the large companies. On an average, for all deciles groups, in the year 2005-2006, mean OTE, PTE and SE are highest and for the year 2003-2004, the lowest.



Source: Computed by author from CMIE, Prowess database

Figure 3.
Mean PTE according to size



Source: Computed by author from CMIE, Prowess database

Figure 4.
Mean SE according to size

4. Conclusion and implications

The results and analyses demonstrate that the mean efficiency of the software industry in India is quite low. The industry is wasting about 35 per cent of inputs. Therefore, there is urgent need for improving the utilization of inputs in this industry. The mean OTE scores demonstrated statistically significant difference across ownership categories. It was observed that the Indian-owned companies have relatively high efficiency score as compared to foreign owned and group owned companies. The better performance of PI companies may be attributed to diasporic effect and in this category the owner his/her self as a workers, so puts more efforts to improve efficiency. The lower efficiency for foreign owned and group owned companies may be due to these companies only caters to their parent companies or groups, and act as back office to operate at the lower end of the value chain. This also hinders them to take advantage of SE. In terms of, size it is observed that medium sized companies performance better. Software industry in India, which is doted by large number of small firms in the lower part of the size pyramid, needs to increase their size to improve their efficiency.

The continuous emphasis of the software industry to cater to the low end of value chain is another cause of concern. The current business appears to be profitably attractive, as the firms work only on the orders received which implies an absolutely assured market for the product. Nevertheless, besides keeping them down as satellite to overseas clients, rather than developing them into future oriented companies having independently developed proprietor software and other IT-enabled products, it also makes them vulnerable to off-shore recessionary trends due to heavy concentration of clients in USA and Europe. This tendency to remain stuck to the outsourced business is not typical of the small companies only but has also trickled down to the large companies which use their organizational capabilities, depth and connectivity to a larger clientele base to get more projects than using these competencies to develop independent proprietor products. Nevertheless, the recent waves of recessions has prompted these companies to look beyond the outsourced business and some of them have starting developing proprietary software products for the domestic market as well which though is still weak yet may develop faster in coming times. Here probably it is the market and the business considerations which may introduce some corrections.

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