

Total Factor Productivity of the Software Industry in India

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सत्यमेव परमो धर्मः

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ABSTRACT

This paper uses the Malmquist Productivity Index (MPI) to estimate change in total factor productivity (TFP) and its constituent components for software companies in India during 1999–2008. On average, the software industry in India has gained productivity by 0.4 per cent; it recorded the lowest technical change in 2005–06 and the highest in 2003–04. Export and human capital were found the most important factors of TFP growth. Older companies have better TFP growth than new companies, and the productivity growth of Indian-owned companies is better than group-owned companies. The coefficient of initial overall efficiency score was found to be negative and statistically significant, indicating that the companies which had initially low level of efficiency had improved upon TFP growth. Companies that initially had low efficiency improved their TFP growth. Research and development (R&D) has little role in the growth of TFP, probably because Indian software companies cater to the lower end of the value chain.

Keywords: Software industry in India, total factor productivity, data envelopment analysis, Malmquist Productivity Index

1 INTRODUCTION

India has achieved remarkable global brand identity in the software sector. The success of this industry is best understood through its contribution to the services sector in the structural transformation of the Indian economy. The software sector contributed about 7.14 per cent to India's GDP in 2011–12 (half the share of agriculture) and 0.6 per cent in 1997–98. Its share in the service sector GDP was 28 per cent in 2011–12 and 5 per cent in 2011–12. This indicates the rising importance of the software sector in the Indian economy. The industry recorded a compound annual growth rate (CAGR) of about 49 per cent for the past three decades (1980–2011) and a CAGR of about 69 per cent in the 1990s (Table 1).

Table 1 CAGR of IT-ITES industry

Time Period	Exports	Domestic	Total
1980–91	50.3		50.3
1991–2000	59.8		69.3
2000–12	25.7	20.6	24.5
1991–2012	40.5		41.9
1991–98	59.8		69.3
1998–2012	30.6	21.6	28.1
1980–2012	47.2		49.0

Source: NASSCOM

However, there has been a deceleration since 2000. Besides this sluggishness, with the increasing integration of India with the global economy and the availability of competent manpower at relatively low cost, many foreign players have entered the Indian market and exposed software companies in India, especially export-oriented ones, to increasing competition. This development raises the question: can Indian software firms survive and grow? One probable solution is raising productivity significantly, but this needs to be investigated in the light of its record and other empirical evidence of improvement in productivity.

The present study endeavours to answer the following questions:

- Is there any increase in the technical efficiency (TE) of software companies in India?
- What are the trends in and determinants of TFP?
- Are Indian-owned software companies more productive than foreign companies in India?

The present study estimates TFP change and its constituent components such as TE change, scale efficiency (SE) change, and allocative efficiency change of software companies in India during 1999–2008 by applying data envelopment analysis (DEA) models (Charnes,

Cooper, & Rhodes 1978; Banker, Charnes, & Cooper 1984). It uses the MPI to estimate TFP, technical change, and efficiency change. The MPI and its constituents compare changes in productivity across two consecutive years. If the value of the MPI or any component of it is above one, then it implies improvement in the performance and vice versa.

Accordingly, this paper is divided into six sections. Section 1 has reported the introduction and motivation of the paper. Section 2 presents the methodology applied for carrying out the research. Section 3 presents the basic results of the analysis. Section 4 examines the relationship among efficiency, technical change, and change in TFP. Section 5 attempts to find out the determinants of TFP growth in software industry in India. Finally, Section 6 reports the conclusion of the study.

2 METHODOLOGY: THE MALMQUIST PRODUCTIVITY INDEX (MPI)

This section elaborates the theoretical construct of MPI. For this, let $x_t = (x_1^t, x_2^t \dots x_n^t) \in R_+^N$ be vector of n inputs producing $y_t = (y_1^t, y_2^t \dots y_m^t) \in R_+^M$ a vector of m outputs in time period t . Let's define production technology P^t for each time period $t= 1, 2, \dots, T$ and is given by:

$$P^t = \{(x^t, y^t) : x^t \text{ can produce } y^t\} \dots\dots\dots 1$$

P^t provides all possible combinations of y^t that can be produced from input vector x^t . Hence, the output distance function is defined as:

$$D_o^t(x^t, y^t) = \min\{\theta : x^t, y^t / \theta \in P^t\} \dots\dots\dots 2$$

The distance function as defined in equation 2 is the reciprocal of Farrell's (1957) measure of output based technical efficiency (Coelli et al. 2003). This observation permits to decompose TFP into two parts, i.e., technical change (TC) and scale efficiency (SE). $D_o^t(x^t, y^t)$ is the DEA efficiency using x^t inputs and y^t outputs.

To define, a MPI requires definition of distance functions with respect to two different time periods and they are given as:

$$D_o^t(x^{t+1}, y^{t+1}) = \min\{\theta : x^{t+1}, y^{t+1} / \theta \in P^t\} \dots\dots\dots 3$$

$$D_o^{t+1}(x^t, y^t) = \min\{\theta : x^t, y^t / \theta \in P^{t+1}\} \dots\dots\dots 4$$

$$D_o^{t+1}(x^{t+1}, y^{t+1}) = \min\{\theta : x^{t+1}, y^{t+1} / \theta \in P^{t+1}\} \dots\dots\dots 5$$

The distance function given in equation 3 represents the maximum proportional change in output vector y^{t+1} required to make (x^{t+1}, y^{t+1}) feasible when the technology of time period t is used. Similarly, one can interpret other distance functions. Analogously, four input distance functions are:

$$D_i^t(x^t, y^t) = \max\{\theta : x^t, y^t / \theta \in P^t\} \dots\dots\dots 2a$$

$$D_i^t(x^{t+1}, y^{t+1}) = \max\{\theta : x^{t+1}, y^{t+1} / \theta \in P^t\} \dots\dots\dots 3a$$

$$D_i^{t+1}(x^t, y^t) = \max\{\theta : x^t, y^t / \theta \in P^{t+1}\} \dots\dots\dots 4a$$

$$D_i^{t+1}(x^{t+1}, y^{t+1}) = \max\{\theta : x^{t+1}, y^{t+1} / \theta \in P^{t+1}\} \dots\dots\dots 5a$$

Given the distance functions, Caves, Christensen, & Diewert (1982) define input-based MPI for time period t as:

$$M_i^t = \frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \dots\dots\dots 6$$

And for time period $t+1$, MPI is given as:

$$M_i^{t+1} = \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^t, y^t)} \dots\dots\dots 7$$

However, the distance function used to define MPI may be either output-oriented or input-oriented. It depends on the statement of the problem of the decision-making units (DMUs) of which productivity is to be estimated. Further, the difference between MPI scores based on input or output orientation is very small (Coelli et al. 1998). The present study has applied an input-oriented measure to examine productivity and its component growth in software industry in India. Thus, henceforth, the present study will not use the subscript to denote output- or input-oriented method.

Fare et al. (1997) use the geometric mean of the above two equations (6 and 7) to produce the MPI. They decompose the MPI into two components, one measuring the change in technical efficiency (catching up effect) and the second one measuring the TC (frontier shift). Relaxing Caves et al.'s (1982) assumption that $D^t(x^t, y^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ equal to one and allowing for technical inefficiency, Fare et al. (1994) provided MPI, which measures the productivity change of a particular DMU in time period t and $t+1$ and is defined as:

$$M^t(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} * \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{1/2} \dots\dots\dots 8$$

This represents the productivity of production point (x^{t+1}, y^{t+1}) relative to the production point (x^t, y^t) , where $D^t(x^t, y^t)$, $D^{t+1}(x^{t+1}, y^{t+1})$, $D^t(x^{t+1}, y^{t+1})$ and

$D^{t+1}(x^t, y^t)$ are the distance functions. The first two are related to the same period whereas the last two are inter-temporal comparisons. A value of M^t greater than unity ($M^t > 1$) indicates positive TFP growth (i.e., productivity gain) from period t to $t+1$ while ($M^t < 1$) and ($M^t = 1$) represents negative TFP growth (i.e., productivity loss) and no change in TFP from time period t to $t+1$. The catching up effect is defined as:

$$Catch-up(C) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \dots\dots\dots 9$$

And the frontier shift effect is defined as:

$$Frontier-shift(F) = \left[\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} * \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \right]^{1/2} \dots\dots\dots 10$$

Now, $M^t(x^{t+1}, y^{t+1}, x^t, y^t)$ can be defined as:

$$M^t(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \right] * \left[\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} * \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \right]^{1/2} \dots\dots\dots 11$$

That is, $M^t(x^{t+1}, y^{t+1}, x^t, y^t) = C * F \dots\dots\dots 11a$

The first component $Catch-up(C) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}$ measures the

change in technical efficiency between periods t and $t+1$, which compares the closeness of the DMU in each period to that period's production frontier. If the value of $C > 1$, it means that DMU has become more efficient in converting its inputs to output in period $t+1$ compared to period t . If $C < 1$, then the DMU becomes less efficient in converting its inputs to output in period $t+1$ compared to period t . If $C = 1$, then there is no change in the technical efficiency of the firm, i.e., the DMU has same distance from the production frontier in both periods. The second component

$Frontier-shift(F) = \left[\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} * \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \right]^{1/2}$ measures the technical frontier

shift between periods t and $t+1$. If the value is greater than one ($F > 1$), then it suggests that there is technical progress (i.e., more output can be produced at period $t+1$ using input of period t). This may be due to the development of new technology and innovation. In the case of the computer industry, as computer quality improves, more computing power is

produced from the same inputs over time (Jorgenson & Striroh 2008). If the value of F is less than unity, then there is technical regress; and if $F=1$, then there is no shift in the technical frontier, i.e., the same output will be produced at time period $t+1$ using inputs of time period t .

Further, to evaluate the impact of scale size (economy of scale) on productivity change, the technical efficiency change can be further decomposed into two components, viz., pure technical efficiency change (PTEC) and scale efficiency change (SEC), i.e., $C=PTEC*SEC$. Now, putting this in equation 11a, we have

$$M^t(x^{t+1}, y^{t+1}, x^t, y^t) = PTEC * SEC * F \dots\dots\dots 12$$

The PTEC compares the closeness of DMU in each period to that period's production possibility frontier (PPF) corresponding to variable returns to scale (VRS). If the distance between the PPF and the DMU has declined over time, then the value of PTEC will be greater than unity; if it increases, then it will be less than unity; and if the distance remains the same, PTEC is zero. Thus, if the value of $PTEC>1$, the DMU is converting its inputs more efficiently to output in time period $t+1$ as compared to time period t .

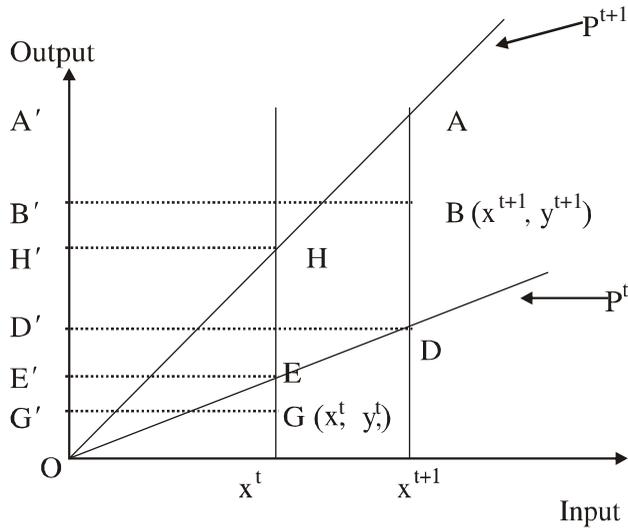
The SEC reflects the impact of any change in scale size of DMU on its productivity. If $SEC>1$, then it means DMU is more scale-efficient in time period $t+1$ than it was in time period t . This suggests that the increase in the productivity of the DMU is attributed to its scale of operation over time. Thus, if the DMU enhances its production, it will result in more productivity. This may be because the DMU was operating at increasing returns to scale in time period t and now it is operating at diminishing returns to scale. If the value of $SEC<1$, it implies that DMU is less scale efficient in time period $t+1$ than time period t , i.e., the decline in its productivity attributes to the change in its scale size, while $SEC=1$ means that scale efficiency is the same over time. However, it does not necessarily mean that the DMU has the same scale size in both periods. Rather, its impact of scale size on its productivity remains the same over time.

2.1 Graphical Representation of Malmquist Productivity Index

2.1.1 Constant returns to scale

The main concepts of MPI in a single input and single output under constant returns to scale (CRS) are presented in Figure 1.

Figure 1 Malmquist Productivity Index under constant returns to scale



The MPI under CRS technology indicates a rise in potential productivity as the PPF shifts from time t to $t+1$. Let the output be y and input x , and the production functions are P^t (Point G) and P^{t+1} (Point B) at time periods t to $t+1$ respectively. Point G represents the input-output combination (x^t, y^t) at time period t and point B (x^{t+1}, y^{t+1}) shows input-output combination at time period $t+1$. The MPI and its components are represented by distance functions where the output distance function along the vertical axis is taken to illustrate MPI.

$$D_o^t(x^t, y^t) = OG' / OE' \dots\dots\dots 13$$

$$D_o^t(x^{t+1}, y^{t+1}) = OB' / OD' \dots\dots\dots 14$$

$$D_o^{t+1}(x^t, y^t) = OG' / OH' \dots\dots\dots 15$$

$$D_o^{t+1}(x^{t+1}, y^{t+1}) = OB' / OA' \dots\dots\dots 16$$

The catch-up effect from time period t to $t+1$ is measured by the following formula:

$$Catch-up(C) = \frac{\text{Efficiency of } (x^{t+1}, y^{t+1}) \text{ with respect to } P^{t+1}}{\text{Efficiency of } (x^t, y^t) \text{ with respect to } P^t} \dots\dots\dots 17$$

Thus, from the graph:

$$\text{Catch-up}(C) = \frac{OB' / OA'}{OG' / OE'} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \dots\dots\dots 18$$

Now, consider the frontier shift case: in Figure 1, the reference point E (x^t, y^t) moves to point H on the frontier of time period $t+1$. Thus, the frontier shift effect at (x^t, y^t) is evaluated as:

$$F1 = \frac{OE'}{OH'} = \frac{OE' / OG'}{OH' / OG'} = \frac{\text{efficiency of } (x^t, y^t) \text{ with respect to } P^t}{\text{efficiency of } (x^t, y^t) \text{ with respect to } P^{t+1}} \dots\dots\dots 19$$

Similarly, the frontier shift effect at (x^{t+1}, y^{t+1}) is evaluated as:

$$F2 = \frac{OD'}{OA'} = \frac{OD' / OB'}{OA' / OB'} = \frac{\text{efficiency of } (x^{t+1}, y^{t+1}) \text{ with respect to } P^t}{\text{efficiency of } (x^{t+1}, y^{t+1}) \text{ with respect to } P^{t+1}} \dots\dots\dots 20$$

The frontier shift is the geometric mean of F1 and F2 and it is given as:

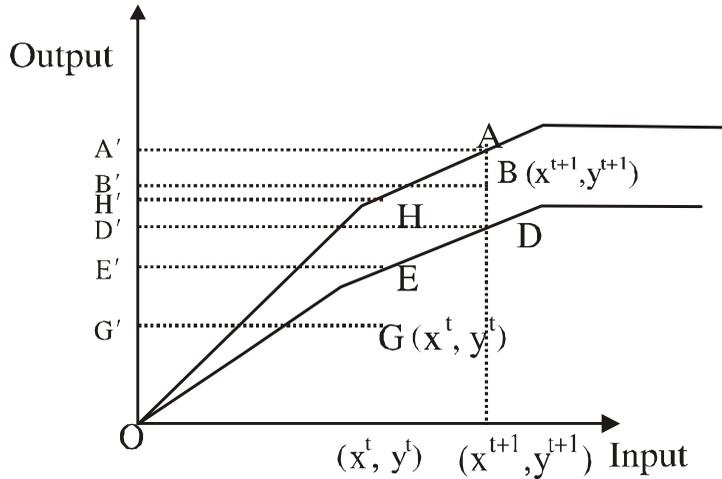
$$F = (F1 * F2)^{0.5} = \left[\frac{OE'}{OH'} * \frac{OD'}{OA'} \right]^{0.5} = \left[\frac{OE' / OG'}{OH' / OG'} * \frac{OD' / OB'}{OA' / OB'} \right]^{0.5} = \left[\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} * \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \right]^{0.5} \dots\dots\dots 21$$

The frontier shift measures the relative distance between technologies of time periods t and $t+1$, in terms of relative efficiency for the same observation measured against two different frontiers.

2.1.2 Variable returns to scale

More often than not, CRS does not apply in the real world. Hence, understanding the concept of MPI under the variable returns to scale (VRS) framework is critical. Further, as discussed in the previous section, the present study has assumed VRS technology to estimate efficiency of software companies. Therefore, the main concept of MPI under variable returns is discussed below and presented in Figure 2.

Figure 2 Malmquist Productivity Index under variable returns to scale



In line with equations 13–18, the distance functions under variables returns can be written as:

$$D^t(x^t, y^t) = OG' / OE' \dots\dots\dots 13a$$

$$D^t(x^{t+1}, y^{t+1}) = OB' / OD' \dots\dots\dots 14a$$

$$D^{t+1}(x^t, y^t) = OG' / OH' \dots\dots\dots 15a$$

$$D^{t+1}(x^{t+1}, y^{t+1}) = OB' / OA' \dots\dots\dots 16a$$

Technical efficiency change (TEC) or catch-up is defined as:

$$TEC = Catch-up(C) = \frac{OB' / OA'}{OG' / OE'} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \dots\dots\dots 18a$$

Similarly, technological change or frontier shift can be defined as:

$$Technology\ Change = \left[\frac{OE'}{OH'} * \frac{OD'}{OA'} \right]^{0.5} = \left[\frac{OE' / OG'}{OH' / OG'} * \frac{OD' / OB'}{OA' / OB'} \right]^{0.5} = \left[\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} * \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \right]^{0.5} \dots\dots\dots 21a$$

2.2 Data Sources and Variable Construct

The main data source of the study is Prowess, compiled by the Centre for Monitoring the Indian Economy (CMIE). 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. The input variables are employment, expenditure on computers and electronic equipment, operating expenditure (including expenditure on software, repairs and maintenance of machinery and building, and training expenses etc.), power, fuel (including wheeling charges paid by electricity companies), and water charges. All nominal data sets are converted into constant price by using the wholesale price index (WPI).

2.2.1 Output variable: Sales revenue

Generally, in productivity analyses, the output variable taken is gross value added (GVA), but some empirical studies have used the gross value of output (Chen & Ali 2004). This use is supported by another study (Dogramaci & Adam 1981), as intermediate inputs are insignificant in an industry such as software. Studies specific to the software industry have also used sales and exports to measure its progress. In the case of India, various studies¹ have used sales and export revenue to examine the progress of the Indian software industry. Even studies focussing on other countries such as Ireland (Sands 2005; Brenznit 2005) and Brazil (Botheho, Stefanuto, & Veloso 2005) have measured the output of the software industry by sales revenue. Therefore, this study takes sales revenue as a measure of output.

2.2.2 Input variables

Employment

Labour is an important input for any production process; in the case of a skill intensive industry such as software, it is the most significant input. Although the Prowess database of CMIE reports data on the number of employees, it reports the number of employees as zero for many firms despite positive sales and exports. This fallacy makes the data inappropriate for the purpose of this study. Nevertheless, the Prowess database also provides data on total wages and salaries, which could be used for computing employment data by dividing wages and salaries by the industry wage rate (assuming wages are equal industry-wide). But that assumption is unrealistic, given the well documented evidence of substantial inter-firm wage rate heterogeneity even among narrowly defined industries (Fairris 2005; Groshen 1991). The prevalence of wage rate heterogeneity among firms in the software sector is further corroborated by the very high attrition rate in this industry. The existing literature

¹ Arora et al. 2010; Athreye 2005; Arora et al. 2001; Arora & Athreye 2002; NASSCOM 2011; Kumar 2001; Heeks 1996

suggests that the number of employees of a given firm is highly correlated to its total assets (White & Liu 1998). Thus, in the absence of data on the number of employees, there is a need to identify a variable (such as wages and salaries) proximate to employment level. There is a high degree of correlation between (1) wages and salaries and (2) total assets because a firm with high total assets may employ more personnel than those with lower 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. The correlation between wages and salaries and the total assets of the firms considered for this study was found to be 0.89. The regression results in this regard are reported in Table 2.

Table 2 Elasticity of wage and salary with respect to total assets

	Coefficients	Standard Error	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 Square	0.775			
Adjusted R Square	0.765			
F-Value	452.9*			0.000
D-W statistics	2.02			
Number of observations	648			

Note: *, **, and *** refer to significant at 1 per cent, 5 per cent and 10 per cent respectively.

It can be seen from the regression result that we have statistically significant F-value, high R-squared value, and close to two Durbin -Watson statistic. This suggests that regression carried out is a good fit. 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.

Expenses on computer and electronic instruments

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

Operating expenditure

Another important input cost in the software industry is operating expense, which includes expenditure on software, repairs, and maintenance of machinery and building, and training of personnel etc. Therefore, for the present study, operating expense is used as an input variable.

Utility expenditure

Utility expenses (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 an input variable for this study.

Since the Prowess database provides data on current prices, the data were converted to constant price series (1993–94 constant prices) by applying WPI, as reported by Reserve Bank of India (RBI). Given that the WPI is not available for the service sector, WPI for industrial workers was taken for converting sales revenue and operating expenditure to constant price series. Similarly, expenses on computer and electronic instruments were deflated by the composite price index (CPI) of computer and computer based systems, and electronic equipment. Utility expenses were deflated by composite price index of fuel and power. Now let us discuss some of the basic results of OTE, technical, and TFP change.

3 BASIC RESULTS AND DISCUSSION

Changes in MPI components of the investigated 72 software companies in India during 1999–2000 to 2007–08—when the service sector led the growth path of the Indian economy—are discussed in this section. These 72 companies accounted for more than 62 per cent of industry revenues; therefore, the results obtained from this exercise can be treated as the overall performance of the industry.

3.1 Overall Technical Efficiency (OTE) change

First, let us look at the overall efficiency change in the industry. Table 3 demonstrates annual averages of OTE, PTE, SE, technical, and TFP changes in the sample companies during the study period. It is evident that OTE change was greater than one only for three years, viz., 2002–03, 2004–05, and 2005–06. For all other years, it was found less than 1. It implies that—except for the aforementioned three years when OTE was found to be improving—it has deteriorated during the remaining years. On an average, there was a 1.3 per cent decline in OTE for the sample companies during the reference period, and this can be attributed to the decline in SE.

Table 3 Malmquist Index summary of annual means

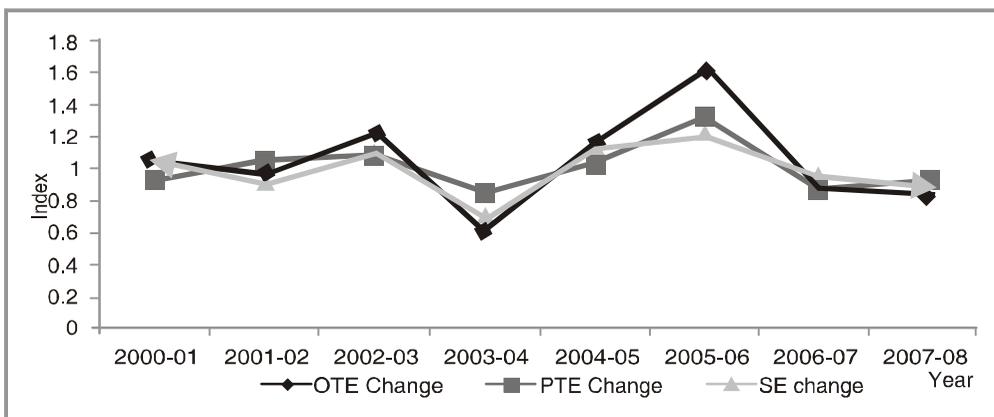
Year	OTE change	TC	PTE change	SE	TFP change
2000–01	0.981	1.044	0.921	1.065	1.025
2001–02	0.962	0.968	1.055	0.912	0.931
2002–03	1.211	0.878	1.095	1.106	1.063
2003–04	0.587	1.715	0.853	0.688	1.006
2004–05	1.161	0.806	1.031	1.126	0.936
2005–06	1.616	0.655	1.335	1.211	1.059
2006–07	0.845	1.231	0.881	0.959	1.04
2007–08	0.847	1.155	0.935	0.905	0.978
Mean	0.987	1.017	1.004	0.983	1.004

Source: Computed from CMIE, PROWESS data set.

Note: Mean is the geometric mean.

Figure 3 also reveals that changes in OTE and SE were in the same direction following the similar pattern, thereby suggesting that change in SE exercised a stronger impact on change in OTE than change in PTE. Therefore, weakening of change in OTE can be attributed to the decline of change in SE. The regressive score of SE change in the software industry in India may be attributed to the fact that this industry is predominantly dotted by the presence of a large number of small companies, which cannot afford to take advantage of scale efficiency.

Figure 3 Change in overall technical efficiency, pure technical efficiency and scale efficiency



Source: Computed from CMIE PROWESS database.

The mean score of OTE change for the whole study period is found to be 0.987, signifying thereby a deceleration of OTE during the study period as is also highlighted by a growth rate of -1.3 per cent in the OTE. The SE was also found to be registering a decline during the study period, as is indicated by its negative growth rate of 1.7 per cent. The most significant progress in OTE and SE was noted in 2005–06, with about 62 per cent and 21 per cent growth rates respectively, while the worst year appeared to be 2003–04 with a negative growth rate of 41.3 per cent and 31.2 per cent respectively. It can be observed from Table 2 that the mean SE change for four years, i.e., 2001–02, 2003–04, 2006–07, and 2007–08 had registered a score of less than one, indicating, on an average, deceleration in SE of sample companies. Further, SE declined by 1.7 per cent on average for the study period.

The change in PTE was found to be greater than one for the study period, with a growth rate of 0.4 per cent. This suggests placid improvement in the PTE scores over the reference period, probably because advancement of computers and other technologies in the software industry helps companies convert their inputs—particularly their labour force—to output more efficiently. There are four years, viz., 2001–02, 2002–03, 2004–05, and 2005–06, when PTE change score was found to be greater than one. For all other years, the change in PTE was found to have decelerated. The year 2005–06 was found to be the most significant in terms of progress in PTE scores with a growth rate of about 33 per cent, whereas for the year 2003–04, there was deceleration in the PTE score with a negative growth rate of about 15 per cent.

In terms of the number of companies whose OTE change was less than one, Table 4 reveals that it went up from 55.56 per cent in 2000–01 to 80.56 per cent by the end of the study period. The percentage of the companies whose OTE change was greater than one in the year 2000–01 declined from 44.44 per cent to 19.44 per cent by the year 2007–08. Similarly, there were 44 companies (61.11 per cent) whose SE change was less than one in the year 2000–01. This had risen to 50 (69.44 per cent) at the end of the study period. The number of the companies whose SE change was greater than one in 2000–01, dropped from 28 (38.89 per cent) to 22 (30.56 per cent) during the study period. A similar pattern was observed for PTE change. This indicated an increase in the number of companies that grew inefficient over the years.

On average, OTE change for the study period was reported greater than one for only 26 companies,² thus indicating an improvement in the TE of these companies. This further reinforces the fact that most of these companies became inefficient over the years, resulting

² 31 Infotech Ltd, Birlasoft Ltd, Blue Star Infotech Ltd, Datamatics Ltd [Merged], Flextronics Software Systems Ltd [Merged], Four Soft Ltd, Geometric Ltd, H C L Technologies Ltd, Hewlett-Packard Globalsoft Pvt. Ltd, Igate Global Solutions Ltd, Infotech Enterprises Ltd, K P I T Cummins, Infosystems Ltd, Mastek Ltd, Megasoft Ltd, Melstar Information Technologies Ltd, Micro Technologies (India) Ltd, Nucleus Software Exports Ltd, Prithvi Information Solutions Ltd, R S Software (India) Ltd, Rolta India Ltd, Satyam Computer Services Ltd, Syntel Ltd, Tech Mahindra Ltd, Teledata Informatics Ltd, Zensar Technologies Ltd and Zylog Systems Ltd.

in the industry becoming more inefficient. This is probably because the software industry in India is booming and returns on investment are greater than in other industries—which might be why the management in the software industry does not spend much effort in improving efficiency. Now, let us examine the TC component of the MPI.

Table 4 Number of companies having scores greater than and less than one in TFP and its components

Year	OTE change		Tech. change		PTE change		SE change		TFP change	
	<1	>1	<1	>1	<1	>1	<1	>1	<1	>1
2000–01	40	32	41	31	47	25	44	28	31	41
	55.56	44.44	56.94	43.06	65.28	34.72	61.11	38.89	43.06	56.94
2001–02	46	26	31	41	39	33	47	25	41	31
	63.89	36.11	43.06	56.94	54.17	45.83	65.28	34.72	56.94	43.06
2002–03	24	48	49	23	35	37	29	43	37	35
	33.33	66.67	68.06	31.94	48.61	51.39	40.28	59.72	51.39	48.61
2003–04	64	8	3	69	49	23	63	9	35	37
	88.89	11.11	4.17	95.83	68.06	31.94	87.50	12.50	48.61	51.39
2004–05	24	48	66	6	35	37	21	51	38	34
	33.33	66.67	91.67	8.33	48.61	51.39	29.17	70.83	52.78	47.22
2005–06	10	62	68	4	26	46	21	51	33	39
	13.89	86.11	94.44	5.56	36.11	63.89	29.17	70.83	45.83	54.17
2006–07	50	22	10	62	58	14	42	30	34	38
	69.44	30.56	13.89	86.11	80.56	19.44	58.33	41.67	47.22	52.78
2007–08	58	14	10	62	56	16	50	22	40	32
	80.56	19.44	13.89	86.11	77.78	22.22	69.44	30.56	55.56	44.44
Avg.	39.5	32.5	34.75	37.25	43.12	28.87	39.62	32.37	36.12	35.87
	54.86	45.14	48.26	51.74	59.90	40.10	55.03	44.97	50.17	49.83

Source: Computed from CMIE PROWESS database.

Note: First row indicates number of companies and second row indicates percentage. Avg. stands for average.

3.2 Technical Change (Frontier Shift)

The Productivity change of any DMU is a combined effect of efficiency change and TC. The preceding sub-sections analysed efficiency changes. The present sub-section presents the TC of the software industry in India. Technical change is the second component of TFP

change and measures the contribution to productivity change of whatever TC (innovation) occurred between time periods t and $t+1$. This index attains a value of greater than, equal to, or less than one if technical progress, stagnation or technical regress had occurred in time period $t+1$ as compared to time period t .

A perusal of Table 2 reveals that the mean TC for the sample companies during the study period was greater than one, i.e., 1.017, suggesting a growth rate of 1.7 per cent in TC, which indicates 1.7 per cent technical progress on average for the sample companies. However, TC was found to be greater than one for four years, viz., 2000–01, 2003–04, 2006–07 and 2007–08, whereas it was less than one for remaining five years, viz., 2001–02, 2002–03, 2004–05, 2005–06 and 2007–08. A perusal of Figure 4 shows a cyclical pattern in the TC for the sample companies for the study period. This may be because software companies in India are susceptible to the world business environment and need to tap technological improvement to remain competitive. For instance, in 2003–04, technical progress was at its highest point when the dotcom bubble burst and slowed down the business environment considerably. Similarly, during 2005–06, mean technical progress had touched the trough especially when the world economy was experiencing a boom. This appears to indicate that the software industry in India preferred technological upgradation only during the lean business period to survive.

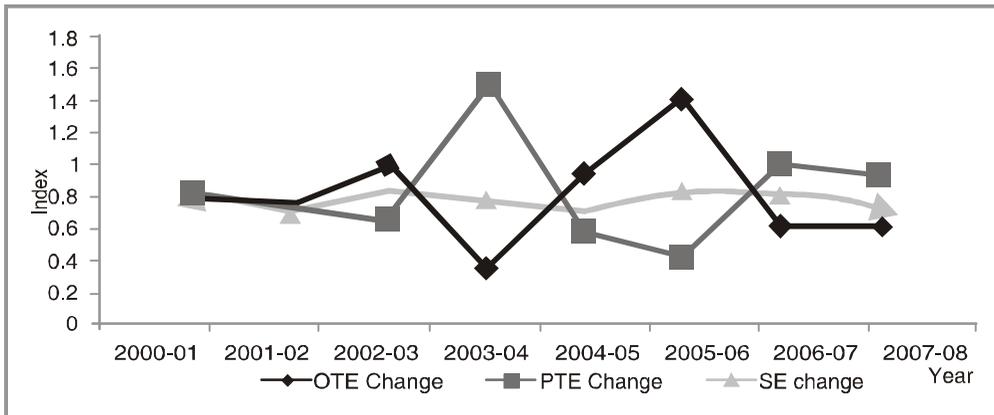
It is evident from Table 4 that on average about 35 companies (48.26 per cent) demonstrated a negative shift in technical frontier, i.e., technical regress, and 37 companies (51.74 per cent) exhibited technical progress during the study period. At the beginning of the study period, there were 41 companies (56.94 per cent) registering technical regress, which came down to 10 (13.89 per cent) by the end of the study period. However, in the year 2005–06, a maximum number of companies had recorded technical regress. Their number stood at 68, comprising 94.44 per cent of the sample. From a total sample of 72 companies, 31 companies making for 43.06 per cent of total had displayed technical progress during 2000–01, which went up to 62 (86.11 per cent) by 2007–08.

On an average, TC of 31 companies (43.1 per cent) was found to be less than one, suggesting that these companies experienced technical regress, whereas about 33 companies (45.8 per cent) appeared to have registered technical progress during the study period as TC scores greater than one. For remaining eight companies that formed 11.1 per cent of the total, average TC scores were found to be one, implying that there was no technical progress for these companies—or that there was regress—and they remained in the same frontier during the whole study period.

It can be observed from Figure 4 that on average, the software industry technology frontier declined by 2 per cent in 2000–01 over 1999–2000, then further declined by 4 per cent in 2001–02 over the preceding year, recording an improvement of 21 per cent in

2002–03 over 2001–02 (Figure 4). However, in the next year, it registered a substantial decline, of 41 per cent, and then progressed by 16 per cent in 2004–05 over 2003–04. It improved 62 per cent the next year, but declined 15 per cent during each of the next two consecutive years. Similarly, the productivity gains on account of TFP change were recorded, on an average, at 2.5 per cent, 6.3 per cent, 0.06 per cent, 6 per cent, and 4 per cent over 1999–2000 to 2000–01, 2001–02 to 2002–03, 2002–03 to 2003–04, 2004–05 to 2005–06, and from 2005–06 to 2006–07 respectively. However, the industry has experienced productivity loss of 6.7 per cent, 6 per cent, and 2 per cent (Figure 11) from 2000–01 to 2001–02, 2003–04 to 2004–05 and 2006–07 to 2007–08 respectively.

Figure 4 Malmquist Index summary of annual means



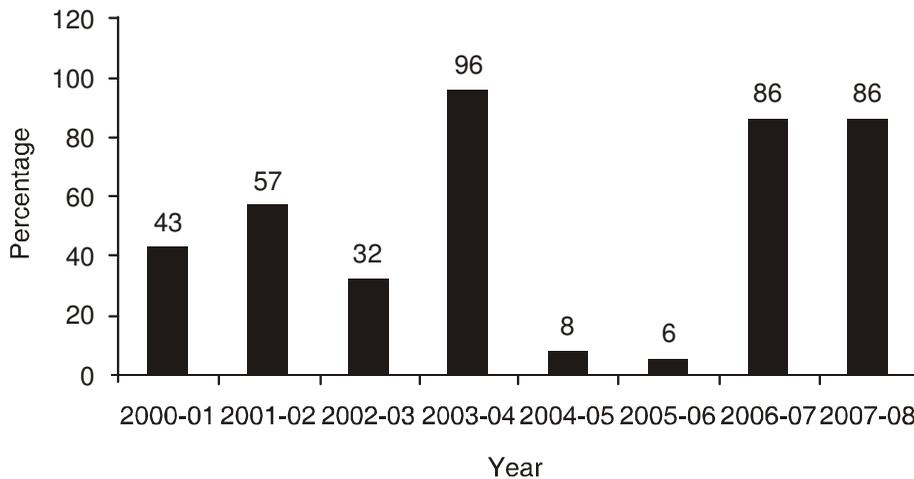
Source: Computed from CMIE PROWESS database.

With respect to individual companies, there were 45 companies³ registering average TC score greater than one, suggesting thereby that these companies on average have improved their technology during the study period. Out of these 45 companies, the total productivity of 24 companies was found to be more than one, implying that there was an enhancement in productivity for those companies. On an average for the reference period, the productivity of the remaining 21 companies has declined despite positive movement in TC, thus suggesting a severe decline in technical efficiency for those companies. But not a single company has registered improvement in technology for all the years under study. Figure 5 reports the percentage of companies with a TC greater than one by year.

³ Accel Frontline Ltd, Aftek Ltd, Aurionpro Solutions Ltd, Aztecsoft Ltd, Compucom Software Ltd, Cybertech Systems & Software Ltd, Datamatics Ltd [Merged], Four Soft Ltd, Genesys International Corpn Ltd, Geodesic Ltd, Geometric Ltd, Glodyne Technoserve Ltd, Goldstone Technologies Ltd, H C L Technologies Ltd, Hewlett-Packard Globalsoft Pvt. Ltd, Hexaware Technologies Ltd, Hinduja Ventures Ltd, Infosys Technologies Ltd, Infotech Enterprises Ltd, K L G Systel Ltd, Mastek Ltd, Megasoft Ltd, Melstar Information Technologies Ltd, Micro Technologies (India) Ltd, Mphasis Ltd, Onward Technologies Ltd, P S I Data Systems Ltd, Panoramic Universal Ltd, Prithvi Information Solutions Ltd, Quinnox Consultancy Services Ltd, Quintegra Solutions Ltd, Ramco Systems Ltd, Rolta India Ltd, S Q L Star International Ltd, Sasken Communication Technologies Ltd, Satyam Computer Services Ltd, Spanco Ltd, Subex Ltd, Tata Elxsi Ltd, Tata Technologies Ltd, Tech Mahindra Ltd, Teledata Informatics Ltd, Tera Software Ltd, Xans a (India) Ltd and Zylog Systems Ltd.

There is no systematic pattern of how many companies have registered a TC score more than one during the study period. During 2003–04, 96 per cent of sample companies had a TC score greater than one, but only 8 per cent⁴ and 6 per cent⁵ (six and four companies) during 2004–05 and 2005–06 respectively. During the last two years of the study period, 86 per cent of companies had improved their technology, as was evident from the greater-than-one TC scores. Now, let us look at the performance of the industry with respect to TFP change.

Figure 5 Percentage of companies with technical change greater than 1



Source: Computed from CMIE Prowess database.

3.3 Change in Total Factor Productivity

The Malmquist TFP (MTFP) index analyses the temporal differences in productivity in time period $t+1$ with respect to time period t . If the value of TFP change is less than one, it denotes regress or deterioration in performance, whereas values greater than one denote improvements. In the present study, the year 1999–2000 has been taken as the technology reference.

It may be noted that the software industry in India has registered productivity progress of 0.04 per cent on average during the study period and for the years 2000–01, 2003–04, and 2006–07, which appear to be the combined effect of an average decline in technical efficiency and an average positive shift in technology frontier. However, during 2002–03

⁴ Aftek Ltd, Computech International Ltd, Goldstone Technologies Ltd, Micro Technologies (India) Ltd, Quinnox Consultancy Services Ltd and Teledata Informatics Ltd.

⁵ Datamatics Ltd [Merged], Geodesic Ltd, Mastek Ltd and Xansa (India) Ltd.

and 2005–06, the average productivity progress observed in the industry appears to be an offshoot of the twin effects of an average improvement in technical efficiency and an average negative shift in the technology frontier. There were average productivity regresses in the industry for 2004–05 and 2007–08, resulting from an average inward shift in the technology frontier and an average improvement in technical efficiency. But the observed productivity regress for 2001–02 was due to an average decline in technical efficiency and an average negative shift of technology frontier.

4 RELATIONSHIP AMONG EFFICIENCY, TECHNICAL AND TFP CHANGES

The relationship among efficiency change, technical change, and TFP change is examined through correlation analysis. Table 5 presents the partial correlation coefficients of annual means of efficiency, technical, and TFP changes. It can be observed that when TC was controlled, correlation coefficients related to change in OTE and SC were found to be positive and statistically significant, suggesting a positive relationship with TFP change and the aforementioned two components of MPI. The correlation coefficient of PTE change and TFP change was observed to be positive but not statistically significant, keeping TC constant, suggesting thereby that even though there is a positive relationship, it cannot be established. The association between OTE change and PTE change was found to be positive and statistically significant when TC is controlled. The partial correlation coefficient between OTE change and SE change was found to be positive but not statistically significant, with TC as control variable, indicating that the association between these two cannot be established.

Table 5 Partial correlation for annual means of efficiency, technical, and TFP changes

Control variable		TFP change	OTE change
TC	OTE change	0.672**	1
	PTE change	0.350	0.846*
	SE change	0.706**	0.431
OTE Change	TC	0.626	—
SE Change	PTE change	—	0.988*
PTE Change	SE change	—	0.982*
TFP Change	TC	—	-0.945*

Note: *, ** and *** refer to significant at 1 per cent, 5 per cent and 10 per cent respectively.

When OTE change was kept constant, the association between TFP change and TC was not statistically significant—even though there is a positive relationship. It appears from the above analysis that efficiency change drives TFP change in the software industry.

When TC was kept constant, the relationship between PTE change and OTE change was found to be positive and statistically significant, whereas the association between SE change and OTE change was observed to be positive but not statistically significant. This suggests that when technology remains the same, big companies take advantage of their size and improve their productivity. This is probably because when more orders come from export markets, larger companies can utilise their inputs, particularly skilled labour force, more efficiently even though there is no improvement in technology.

In the software industry, the association between OTE change and PTE change was positive and statistically significant, when SE change was kept constant and the relationship between SE change and OTE change was found to be positive and statistically significant, with no change. Interestingly, the relationship between OTE change and TC was negative and statistically significant when TFP change remained constant. This indicates that efficiency and TC in the software industry in India do not go hand in hand to improve productivity. But when there is no technological improvement, the industry falls back on efficiency to improve productivity; and when there is an improvement in technology, the industry does not attempt to improve its efficiency. Foreign countries have been giving the Indian software industry steep competition in the competitive world market, and it needs to improve its productivity through both efficiency and TC. To take this analysis further, the mean scores were estimated for all companies during 1999–2008 and Spearman rank correlation was carried out (Table 6).

Table 6 Spearman rank correlation of mean efficiency and technical and TFP changes for sample companies during 1999–2008

	OTE Change	TC	PTE Change	SE change
OTE Change	1	–	–	–
TC	-0.070***	1	–	–
PTE Change	0.611*	-0.023	1	–
SE change	0.497*	-0.028	-0.242**	1
TFP Change	0.875*	0.331*	0.551*	0.446*

Note: *, **, and *** refer to significant at 1 per cent, 5 per cent and 10 per cent respectively.

The rank correlation coefficients of mean efficiency, technical, and TFP changes for sample companies during 1999–2008 indicated a negative and statistically significant relationship between OTE change and TC. This supports the earlier argument that OTE change and TC do not go together in the software industry to improve productivity. This is probably because labour laws and other labour market regulations in India do not allow companies to get rid of their excess labour—a primary input in the software industry—even

when there is a technical improvement requiring substitution of labour by other inputs because of technological innovation or upgradation. The increased expenses on the acquisition of new technology without any corresponding reduction in the labour force might have resulted in the negative efficiency change. In addition, mastering an innovated technology may have a learning period during which the technology change may not demonstrate any improvement in efficiency. Hence, this might lead to negative association between efficiency change and TC.

Further, there is a positive and statistically significant relationship between TFP change and TC; TFP change and PTE change; TFP change and SE change; and TFP change and OTE change. The association between TFP change and TC and between TFP change and PTE change was not statistically significant in the partial correlation analysis but was statistically significant in the case of rank correlation analysis. The relationship between OTE change and PTE change was positive and statistically significant. Similar is the case with SE change. There was negative and statistically significant association between SE change and PTE change, suggesting thereby that when a company is improving its efficiency through better utilisation of the inputs, it does not appear to be also taking advantage of its size to gain efficiency. Table 7 contains further information on the aspects of correlation among different components of MPI.

The year-wise Spearman rank correlation between TFP change and other components of MPI was positive and statistically significant for most part of the study period, with some exceptions. The association between TFP change and TC for one year, i.e., 2003–04, was negative but not statistically significant. This suggests a decline in TFP growth that year, primarily driven by a decline in efficiency change. The efficiency scores of the sample companies were the lowest that year owing to the sluggish global business environment after the dotcom bubble burst. This may be because the slowdown in the international market led to the decline in efficiency change and hence a negative TFP growth, as many software companies were operating on the increasing returns to scale.

Moreover, the association between OTE change and TC was negative and statistically significant for all years and, in absolute terms, the rank correlation coefficient had reached its maximum in 2003–04 with a value of -0.736. This also supports the discussion on the matter in the preceding paragraph. Similarly, the association between TC and the two components of OTE change, i.e., PTE and SE change was observed to be negative for the entire reference period. The association between OTE and PTE changes, and OTE and SE changes was found to be positive and statistically significant for all the years. Now, let us find out the determinants of TFP in the industry.

Table 7 Year-wise Spearman rank correlation of efficiency change, TC and TFP change for sample companies

Year		OTE change	TC	PTE change	SE change
2000-01	TC	-0.170***	1	–	–
	PTE change	0.799*	-0.207***	1	–
	SE change	0.404*	-0.145	-0.079	1
	TFP change	0.819*	0.286*	0.635*	0.441*
2001-02	TC	-0.416*	1	–	–
	PTE change	0.701*	-0.183	1	–
	SE change	0.442*	-0.330*	-0.212**	1
	TFP change	0.815*	0.076	0.672*	0.287**
2002-03	TC	-0.391*	1	–	–
	PTE change	0.703*	-0.160	1	–
	SE change	0.426*	-0.252**	-0.208***	1
	TFP change	0.740*	0.224***	0.561*	0.312*
2003-04	TC	-0.736*	1	–	–
	PTE change	0.535*	-0.248**	1	–
	SE change	0.539*	-0.449*	-0.299*	1
	TFP change	0.615*	-0.041	0.461*	0.275**
2004-05	TC	-0.302*	1	–	–
	PTE change	0.420*	-0.028	1	–
	SE change	0.730*	-0.222*	-0.182	1
	TFP change	0.789*	0.237***	0.422*	0.531*
2005-06	TC	-0.513*	1	–	–
	PTE change	0.520*	-0.173	1	–
	SE change	0.390*	-0.283**	-0.491*	1
	TFP change	0.728*	0.066	0.412*	0.247**
2006-07	TC	-0.384*	1	–	–
	PTE change	0.693*	-0.171	1	–
	SE change	0.565*	-0.410*	-0.024*	1
	TFP change	0.768*	0.167	0.689*	0.283**
2007-08	TC	-0.253**	1	–	–
	PTE change	0.471*	-0.099	1	–
	SE change	0.608*	-0.206***	-0.31	1
	TFP change	0.831*	0.225***	0.470*	0.440*

Note: *, ** and *** refer to significant at 1 per cent, 5 per cent and 10 per cent respectively.

5 DETERMINANTS OF TFP GROWTH

Empirical literature has found heterogeneity of firms within an industry. In addition, the literature reveals a high degree of heterogeneity in productivity across firms even within an industry in both developed and developing countries (Bartelsman and Doms 2000; Tybout 2000). Micro-level studies have examined in detail how individual characteristics drive cross-sectional productivity differentials. Firm-level data have also enabled the estimation of a model that differentiates between economies external to the firm but internal to the industry. In particular, micro-level data allows the assessment of the relevance of each firm-level variable to productivity change. Since productivity change is driven by both TEC and allocative efficiency change, factors that determine the efficiency of firms are supposed to explain productivity change. In other words, factors that explain efficiency change are the determinants of TFP change.

A fair amount of research has been conducted on the determinants of efficiency (and hence determinants of TFP) across industries and national boundaries. The most notable contribution is from Caves (1992) and identifies five determinants of efficiency, viz., competitive conditions, organisational factors, structural heterogeneity, dynamic disturbances, and regulation for manufacturing industries. These determinants per se are decided by some extraneous variables. Competitive conditions are influenced by concentration, import competition, and export intensity. Organisational factors in an industry are determined by variables such as scale of plant, diversification by firms, age, extent of subcontracting, prevalence of foreign investment, and the organisation of the labour force, including the extent of unionisation and the use of part-time employees. On the other hand, structural heterogeneity factors comprise capital intensity, vintage of capital, product differentiation, fuel intensity, regional dispersion, inter-plant dispersion of material-labour ratio, diversity of industry product, diversity of plant scale, and the proportion of non-production workers. It is argued that these factors will cause competing units to exhibit heterogeneous levels of efficiency in the long run. Similarly, dynamic disturbance factors consist of the intensity of R&D expenditure, technology import payment, technology export receipts, rate of productivity growth, rate of output growth, and the variability of output growth. However, these factors can cause a shift in the efficient frontier and the position of the firms relative to the frontier. Finally, regulatory policies such as tariff protection and policies that control the entry of firms in an industry affect all the firms in the same way as in an industry.

Nevertheless, none of the aforementioned factors is relevant to the present study as the software industry is skill-intensive rather than capital-intensive. Further, given the data constraints, only a few variables could be taken up for determining the efficiency of software companies in India. Accordingly, the relevant explanatory variables are explained below.

5.1 R&D Intensity: RDI

Since Schumpeter's seminal work *Capitalism, Socialism and Democracy* (1942), the proliferation of well-documented research studies in this field has established innovation as an engine of growth very well. New-Schumpeterian theories of TC have also highlighted the significant role of innovation and its impact on technical advances (Mensch 1979; Dosi 1982; Freeman et al. 1982). Similarly, the new theoretical literature on innovation-driven growth has also recognised the importance of innovations very well (Romer 1990; Grossman and Helpman 1991; Barro and Sala-i-Martin 1995; Aghion and Howitt 1998). Also, there has been a handful of empirical studies that have explored the role of innovation in growth through productivity change (Frantzen 2003; Sorensen, Kongsted and Marcusson 2003; Benavente J M 2008; Smith et al. 2002; Dilling-Hansen et al. 1998) and concluded in favour of the positive impact of innovation on productivity change.

In the software industry in general, where 75 per cent of the revenue comes from new products (Hoch et al. 2000), innovation becomes an important part of the production processes to survive and grow in an intensely competitive world market. Since companies will be more competitive if they produce at their most efficient level, the present study aims at exploring the extent to which innovations—as measured by in-house R&D expenditure (Stone et al. 2008)—impact a company's efficiency. Although in-house R&D is not the sole measure of innovation and other variables—the number of patents or new products, etc. also measure the innovation of a firm, company, or industry—we cannot use these variables as an appropriate proxy for innovation as data is not available. Therefore, the present study has taken R&D intensity—measured as the ratio of R&D expenditure to sales—as a proxy for innovation.

5.2 Export Intensity

Export is the major component of sales revenue of Indian software companies. Export denotes competition forced onto the company due to outward orientation. The self-selection hypothesis postulates that firms oriented towards the international market are more efficient than those focussing primarily on the domestic market (Handoussa et al. 1986; Haddad 1993; Aw and Hwang 1995; Bernard and Jensen 1995). However, the existing body of literature so far has not been able to firm up unidirectional causation in this regard. Some research studies support the self-selection hypothesis, implying that more efficient firms become exporters, but some other studies emphasise export-induced efficiency gains through learning-by-exporting (Rosenberg 1982; Bernard and Jensen 1995; Clerides et al. 1998). Therefore, it would be appropriate to find the impact of export orientation on the efficiency of the company.

5.3 Royalty Payments: RI

Royalty payment is a common practice in the industry for drawing upon a proprietary technology or software, as the case may be, for manufacturing a quality product or cutting costs. Mostly, companies acquire technology in a disembodied form—by importing designs, drawings, and blueprints—and use them for producing a given output. This helps them to maximise the utilisation of skilled labour force with greater degree of efficiency, apart from maintaining quality and costs. Since software companies worldwide are moving towards higher value-added and more complex software services that necessitate state-of-the-art technology along with more knowledge-intensive manpower, and more managerial and marketing skills, royalty payment for using such proprietary technologies is not out of place. For instance, during 1994–95 to 2001–02, 34 per cent of Indian and foreign IT firms were found paying “lump sum or recurring royalty payment abroad” (Nollen 2004).⁶ Since the use of proprietary software technology and technological alliances does have the potential to improve efficiency, the royalty payment for these, measured as RI, has been taken as an explanatory variable.

5.4 Wages and Salaries (W&S)

The theoretical literature explains how higher wages can improve productivity. Weiss (1980) argued that when a company offers higher wage, it attracts a more productive pool of applicants. Thus, if workers’ productivity depends positively on the wage, firms may find it optimal to pay a wage above the market-clearing level. The empirical literature also suggests that a higher wage may induce workers to work harder (Akerlof 1984). Another possibility of higher wages emerges from labour supply constraints.

Given globalisation, the relatively easy movement of the labour force across national boundaries, and the high attrition rate in the software industry in India, companies must pay their employees higher wages to retain them. Once inducted into a given software company, workers have to undergo intensive training that adds to their work capability and quality. If a worker leaves the company in search of greener pastures after having undergone such training, the time and investment made in the worker is lost. In such situations, the company may prefer to pay higher wages over losing them. An annual wage increase of 20–30 per cent for the past many years in the Indian software industry (Kumar 2001; Carmel 2003) corroborates the contention that companies prefer to improve the pay package by taking stock of the trade-off between worker’s quality and compensation involved rather than taking the risk of employee’s attrition beyond an acceptable level. In view of the above postulation and evidence from the theoretical and empirical literature, wage and salary intensity has been taken as an explanatory variable.

⁶ http://www.iipi.org/reports/india_software.pdf

5.5 Firm Size: SIZE

From a theoretical viewpoint, the impact of firm size on efficiency is not very well established in either direction (Audretsch 1999). For instance, firm size may be negatively impacting efficiency if large firms experience diseconomies in production due to management and supervision problems. On the other hand, in the case of small firms, the direct participation of the firm's owner in the productive process lowers the cost compared to large firms, where delegation gives rise to issues of potential adverse selection and moral hazard. Also, a larger firm focusses more on process, form, and bureaucracy. It has also been reported that larger firms find it difficult to remain efficient (Leibenstein 1966). However, the research literature also testifies that size can impact efficiency positively as large firms may enjoy efficient human specialisation as well as scale economies (Williamson 1970). Further, due to the outcome of selection process "in which efficient firms grow and survive, while inefficient firms stagnate or exit the industry (Jovanovic 1982)" it is more likely that large firms are more efficient than the smaller ones. Besides, larger firms also

- command resources for acquiring high value adding proprietary software technologies;
- have the capacity to churn out larger volume of software products at relatively lower per unit costs; and
- attract much better knowledge-intensive manpower due to career advancement opportunities owing to better work prospects available within and outside the national frontiers.

Although empirical studies on the manufacturing sector in developing countries do not support either direction (Little et al. 1987; Cortes et al. 1987), it appears plausible to assume that size may impact efficiency in a software firm for the reasons cited above. Hence, 'size of the company' measured by its total assets has been taken as an explanatory variable.

5.6 Age of the Firm: AGE

Recent studies on the effects of a firm's age on efficiency do not show a definite direction. For instance, it has been suggested that a firm's productivity varies initially but eventually settles down (Jovanovic 1982). It was further argued that as firms only learn about their true efficiency by operating and producing effectively, a process of natural selection arises whereby less efficient firms leave the industry while more efficient firms grow to their optimal size. On the other hand, the existing body of literature also suggests that older firms may have older capital equipment and may have also developed inefficient production routines and practices along with a rigid bureaucratic structure, leading to a negative impact of age on efficiency.

In the case of the Indian software industry, due to tax-related and other incentives provided by the government for export-oriented software and services firms, new firms enter the export market right from the beginning. Yet, it is very likely that young firms are at the lower end of the technological ladder. It has been suggested that for every large software firm that upgrades from a factor-driven to an investment-driven model, five new small firms enter the industry using the low-barrier body-shopping approach. Thus, it is likely that new companies are less efficient than the old established firms. Therefore, in order to examine the impact of age of the firm on efficiency, AGE has been taken as a dummy variable. The value 1 is assigned if the company was instituted after 1991 and categorised as a new company; otherwise, the value assigned is zero.

5.7 Ownership

It is generally perceived that MNCs have better access than smaller domestic firms to state-of-the-art proprietary software and technologies, which could be why these are far more efficient than domestic firms. Besides, MNCs' better access to financial resources and 'intangible assets' such as technological knowledge, skills, and superior management practices may give them a decisive edge in terms of efficiency (Pitt and Lee 1981). This study also accounts for group-owned companies because these have the capability to pool financial and manpower-related resources, apart from sharing market intelligence, which may give them an edge over single private Indian/foreign-owned companies. Therefore, it would be interesting to find out how a company's ownership impacts its efficiency. For this purpose, companies included in the sample have been divided into (1) private Indian companies, (2) private foreign companies, and (3) group-owned companies. The ownership is represented by dummy variables with group-owned companies as the reference point.

From the above discussion, the conceptual framework, as given below

Efficiency=f (R&D intensity, export intensity, wages and salary intensity, age, size, royalty intensity, dummy for Indian and foreign-owned companies).

Following the above conceptual framework for the determinants of efficiency, the firm-specific variables taken as the explanatory variables for determining productivity growth are R&D intensity, export intensity, wages and salary intensity, age, size, royalty intensity and dummy for Indian and foreign-owned companies. The initial level of efficiency is also taken as an independent variable to examine whether the productivity of initially more efficient firms has improved more than that of initially less-efficient firms. Also, two dummy variables were taken as explanatory variables for firms operating on increasing returns to scale (IRS) and diminishing returns to scale (DRS), as the case was, to investigate their TFP growth. From the above discussion:

$$\text{TFP growth (TFPG)} = f \left(\begin{array}{l} \text{R \& D intensity (RD), export intensity (EX), wages and salary intensity (W),} \\ \text{age, size, royalty intensity (RI), dummy for Indian (D1) and foreign (D2) owned} \\ \text{companies, initial level of overall efficiency (OTE), dummy for companies operating} \\ \text{in IRS (D3) and DRS (D3)} \end{array} \right)$$

Mathematically, this can be written as:

$$\begin{aligned} \text{TFPG}_{it} = & \mu_i + \beta \text{RD}_{i,t-1} + \delta \text{EX}_{i,t-1} + \varepsilon \text{W}_{i,t-1} + \phi \text{age}_{i,t} + \varphi \text{size}_{i,t-1} \\ & + \gamma \text{RI}_{i,t-1} + \eta \text{OTE}_{i,99} + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_3 D_3 + \lambda_4 D_4 + u_{it} \end{aligned} \quad \text{.....25}$$

where ‘i’ stands for cross-section units, i.e., firms/companies;

‘t’ stands for time period;

u_{it} is the error term;

$\text{OTE}_{i,99}$ is the overall efficiency score of ‘ith’ firm in the year 1999–2000, i.e., beginning of the study period; and

μ_i is the firm-specific intercept.

The independent variables (such as R&D intensity, export intensity, wages and salary intensity, and size) were taken with one-year time lag because these variables were unlikely to affect TFP growth contemporaneously. In addition to this, to avoid the endogeneity problem, a one-year time lag was taken. For instance, productivity increases might cause an increase of wages through rent-sharing. $D_1=1$, if the ownership of the company is private Indian, otherwise zero. $D_2=1$, if the ownership of the company is foreign-owned, otherwise zero. Thus, the group-owned companies were taken as the reference. $D_3=1$, if the company is operating under the IRS in the time period ‘t-1’, otherwise zero. $D_4=1$, if the company is operating under DRS in the time period ‘t-1’, otherwise zero. Hence, the companies operating under CRS were considered as the reference.

Since the data set is panel in nature, applications of regression technique raise some issues such as the possibility of the existence of spurious correlation due to non-stationary data, omitted variables, endogeneity, and reverse causality, which may lead to biased estimation of coefficients. Although the problem of non-stationarity could be addressed by applying regression in first difference, this may reduce the information considerably and remove the long-run characteristic of variables. The most plausible solution under such constraints could be the application of fixed effect model on non-stationary panel data, as it facilitates the handling of omitted variables and endogeneity bias. Furthermore, this estimation method addresses the problem of non-stationarity to some extent for the reason that in the ‘within form’, deviations from the mean are used in the estimation (Mitra and Sharma 2011; Baltagi 2005).

Prior to examining determinants of TFP growth, the relevant variables were tested for stationarity. There are various panel unit root tests available to examine the stationarity in any panel data set. Among those, the most common tests in practice are Levin and Lin (1993) (LL); Im-Pesaran-Shin (1997, 2003) (IPS); and Maddala-Wu (1999) (MW). The procedures developed by Quah and by Levin and Lin suffer from restrictive assumptions. The Quah procedure does not account for the heterogeneity across groups such as individual, specific effects and different patterns of residual serial correlation. The LL test allows for individual, specific effects and dynamic heterogeneity across groups but bases upon a very strong assumption that N/T tends to be zero, where N is the number of cross section units and T is number of time periods. However, IPS test, which is akin to the LL test, with a less restrictive assumption of $N/T=k$, where k is a positive constant, could be used as an alternative. Given that in the present study $N=72$ and $T=9$, it appears that the IPS test is more appropriate. Hence, it has been applied to examine the stationarity here despite Breitung (1999) having had reported that IPS suffers a dramatic loss of power when individual trends are included, and the test is sensitive to the specification of deterministic trends. Maddala and Wu (1999) have, nevertheless, argued that the value of the MW test does not depend on different lag lengths in the individual ADF regressions and, therefore, the MW test is superior to the IPS test. The present study, therefore, has applied both IPS and MW tests to examine stationarity.

For stationarity of a panel variable, say Y_{it} , the following regression equation was given by IPS:

$$\Delta Y_{i,t} = \alpha_i + \rho_i Y_{i,t-1} + \varepsilon_{i,t} \dots\dots\dots \bar{t} = \frac{1}{N} \sum_{i=1}^N \tau_i$$

Where $i=1, 2..N$, and $t=1,2.....T$. IPS has proposed the null and alternative hypothesis that

$$H_0: \rho_i = 0 \text{ for all 'i', and } H_1: < 0$$

Thus, under the null hypothesis, all series in the panel are non-stationary processes; under the alternative, a fraction of the series in the panel is assumed to be stationary. This is in contrast to the LL test, which presumes that all series are stationary under the alternative hypothesis. IPS also propose the use of a group–mean bar statistic, where the statistics from each ADF test are averaged across the panel; again, adjustment factors are needed to translate the distribution into a standard normal distribution under the null hypothesis. IPS demonstrates that it has better finite sample performance than LL test. The simplest test proposed by IPS, the so called t-bar statistic, is defined as the average of the individual Dickey-Fuller (DF) or augmented Dickey-Fuller (ADF), τ statistics.

$$\text{, where } \tau_i = \frac{\hat{\rho}_i}{\hat{\alpha}_{\hat{\rho}_i}} \dots\dots\dots 27$$

From equation 6.27, the IPS statistic is:

$$t_{IPS} = \frac{\sqrt{N}(\bar{t} - E[\tau_i | \rho_i = 0])}{\sqrt{Var[\tau_i | \rho_i = 0]}} \dots\dots\dots 28$$

The MW statistic is given by:

$$P = -2 \sum_{i=1}^N Ln p_i \dots\dots\dots 29$$

where p-values are from individual ADF tests.

The P test is distributed as chi-square with degrees of freedom twice the number of cross-section units, i.e., 2N, under the null hypothesis. The unit root test was obtained by using Eviews-7 statistical software. The results of the unit root tests are reported in Table 8. For all individual series, the hypothesis of unit root is rejected at the level, indicating thereby the stationarity of variables at their levels.

Table 8 Panel unit root test result

Variables	Levels	
	IPS-statistics	MW-statistics
TFP growth	-6.02*	83.86*
Export intensity	-5.84*	62.04*
Wages and salary intensity	-7.18*	95.42*
Size	-4.53*	58.33*
Royalty intensity	-11.43*	113.56*
R&D intensity	-10.87*	111.02*

Note: The critical values for MW test are 37.57 and 31.41 at 1 per cent and 5 per cent statistical levels, respectively. *Signifies rejection of the unit root hypothesis at 1 per cent level.

Given that the variables are stationary at their levels, initial equation 25 was estimated by least square dummy variable (LSDV) of fixed effect model to examine the determinants of TFP growth. The LSDV model captures the heterogeneity among the cross-sectional units and also the unobserved effects such as managerial capability etc. In the LSDV model, the company ‘PSI Data Systems Ltd’ was taken as the reference because it lies in the middle with respect to the mean TFP change for the entire period. However, the result indicated that the F-statistics was not statistically significant and the adjusted R square was found to be negative.⁷ Hence, the present study has applied the pooled regression. This model does

⁷ The F-statistics was found to be 0.879, significant level was 89.5 per cent, and the adjusted R-square found to be -0.017.

not use dummy variables and thus has larger degrees of freedom than that of LSDV. For the estimation, Limdep statistical software was used and the possible auto-correlation correction was removed. It may be pointed out here that since two independent variables, i.e., export intensity, and wage and salary intensity measuring human capital are highly correlated, two models were estimated and the results are reported in Table 9.

Table 9 Determinants of TFP growth of software industry in India

Variables	Model-1		Model-2	
	Standardised coefficients	Prob.	Standardise coefficients	Prob.
Constant	0.783*	0.000	1.069*	0.000
Export intensity	—	—	0.997*	0.000
Age	0.112*	0.000	0.001*	0.000
Dummy for Indian-owned companies	0.005***	0.076	0.005***	0.089
Dummy for foreign-owned companies	-0.008	0.741	-0.001	0.652
Size	0.027	0.617	0.00008	0.940
Wages and salary intensity (Human capital)	0.756*	0.000	—	—
Royalty	0.003***	0.062	0.002***	0.070
R&D	-0.022	0.489	-0.003	0.569
Dummy for companies operating on IRS	0.013***	0.097	0.012**	0.016
Dummy for companies operating on DRS	-0.011	0.306	0.005	0.363
Initial overall efficiency	0.011**	0.029	-0.006**	0.037
F-Statistics	1161.268*	000	1197.4*	000
R square	0.752		0.950	
Adjusted R square	0.749		0.947	
Durbin-Watson (D-W) statistic	1.98		2.07	
Akaike information criteria	-3.24		-356	
Number of observations	576		576	

Note: *, **, and *** refer to significant at 1 per cent, 5 per cent and 10 per cent respectively.

It can be observed from Table 9 that the adjusted R square value is reasonably high, F-statistics statistically significant, and close to two Durbin-Watson statistics in both models—suggesting that the models are a good fit. Since the coefficients reported in Table 9 are standardised, coefficients can be compared across variables. It is interesting to note that in model 1, it is the human capital measured by wages and salary intensity that had a stronger impact on TFP growth than other variables. Similarly, in model 2, export intensity exercised

a stronger impact on TFP growth than that of other variables. Further, the coefficient of export intensity is 0.241 points higher than coefficient of human capital—indicating exports are more important than human capital for TFP growth in the software industry. This is probably because—as in other industries and sectors—exports induce productivity growth⁸ when firms adapt to advanced technologies through exports and advance technology to compete in foreign markets.⁹ In addition, firms also learn by doing, and the expansion of production because of exports—reduces unit cost as most software companies were operating under IRS. Moreover, given the lower-end skill level of Indian software professionals, human capital had less impact on TFP growth than exports. Nevertheless, as evident from their statistically significant positive regression coefficients, both are important factors that explain the TFP growth of the Indian software industry. Exports have no impact on overall efficiency but a strong impact on TFP growth, suggesting that the spillover effect of exports on technology has contributed towards improvement in TFP.

The explanatory variables (age, dummy for Indian-owned companies, royalty intensity, and dummy for companies operating on IRS) have positive and statistically significant coefficients, suggesting that these were instrumental in promoting TFP growth in the Indian software industry during 1999–2000. This indicates that software companies that spent more on royalty improved productivity more than companies that spent less on royalty. This is probably because royalty payments indicate that the intermediate software or technology acquired facilitated production and hence increased productivity. The positive and statistically significant coefficient of age suggested that older companies have better TFP growth than new companies. This may be because older companies have learnt more by doing and because they had already established their export credentials. Higher exports, on their part, appeared to have enhanced their productivity through export externalities as well. Coupled with the positive impact fact it has on TFP growth, this indicates that age has a very strong positive impact on TC, which overrides its negative impact on efficiency to have an overall positive impact on TFP growth. A statistically significant and positive coefficient for Indian-owned companies suggests that productivity growth in these companies was better than in group-owned companies, probably because associate firms assure the group of a market, and therefore the group has no compulsion to improve efficiency. Last but not least, companies operating under IRS have been found to have better productivity growth than those operating under CRS.

The coefficient of initial overall efficiency score was found to be negative and statistically significant, indicating that the companies with an initial low level of efficiency recorded better TFP growth. This could be an outcome of the push effect of the competition

⁸ Baldwin and Gu 2003; Bonelli 1992; Haddad, De Melo and Horton 1996; Weinhold and Rauch 1997; Yean 1997; Sjoeholm 1999

⁹ Balassa 1978; Krueger 1980; Nishimizu and Robinson 1982

requirement in the global market, which forced them to improve their efficiency if they wanted to survive intensifying global competition and grow. The coefficients of all other variables are not statistically significant; hence, their relationship cannot be established. The coefficient of R&D intensity was negative but not statistically significant; hence, their relationship cannot be established. This may be because Indian software companies operate at the lower end of the value chain.

7 CONCLUSION

This paper examines change in MPI and its constituent components and finds that the Indian software industry has gained productivity by 0.4 per cent on average. The industry recorded the lowest TC in the year 2005–06. During 1999–2008, export was found to be more important for TFP growth than human capital. Nevertheless, both are the most important factors that explain TFP growth, as is evident from their statistically significant positive regression coefficients. Additionally, the explanatory variables such as age, dummy for Indian-owned companies, royalty intensity, and dummy for companies operating under IRS were also found to bear positive and statistically significant coefficients, suggesting thereby that these variables were instrumental in promoting TFP growth. Older companies have better TFP growth than new companies, and the productivity growth of Indian-owned companies is better than group-owned companies. The coefficient of initial overall efficiency score was found to be negative and statistically significant, indicating that the companies which had initially low level of efficiency had improved upon TFP growth. Research and development has little role in promoting TFP growth in the industry.

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