Eurasian Journal of Business and Economics, 17(34), 65-92, (2024).

Performance Analysis of the Indian IT & ITeS Sector: An Application of Additive-DEA and G2SLS

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Received: June 21, 2024. **Revised:** November 16, 2024. **Accepted:** November 24, 2024.

Abstract

This study uses an integrated balanced scorecard-based Additive-DEA framework to identify proxy variables for the inputs and outputs for a sample of firms in India's information technology and information technology-enabled services sector to identify and analyse these firms' inefficiencies. The additive-DEA model is used because it is invariant to data translation, in addition to being non-radial and non-oriented, and hence can deal with negative values of variables that are critical to analyse in(efficiency). This is the first such study in the Indian context that focuses on dealing with negative values for earnings as one of the output variables. The results show that high-performing firms, as calculated by the Additive-DEA method, have higher financial gains in terms of revenue, earnings, and return on equity. Further, the study also attempts to explain the factors influencing the firms' performance using a regression framework for which a generalised two-stage least square method is used. The regression results show that firm characteristics like age, industry specialisation, and business type have no influence on firm performance, while factors like exports, exchange rate changes, and market focus impact its performance. These results have critical policy implications for this sector to reduce inefficiency by controlling costs and increasing spending on research and development.

Keywords: *Additive-DEA; BSC-DEA; IT&ITeS; India; Efficiency.*

JEL Classification Codes: *C610, L860*
UDC: *338.001.36*
DOI: https://doi.org/10.17015/ejbe.2024.034.04

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1. Introduction

The Information Technology and Information Technology-enabled Services (IT & ITeS) sector in India began to grow at unprecedented rates since the launch of economic reforms in 1991, depending primarily on exports of IT & ITeS services to the developed countries (Murthy, 2011). According to NASSCOM, exports from this sector reached USD 178 billion in 2021-22. Given India's perennial deficit on the balance of trade account and a surplus on the invisibles account, the export of services by this sector is the most dominant determinant of surplus on the invisibles account. In addition, this sector has been significantly contributing to India's GDP, FDI inflows, and employment generation for skilled, semi-skilled, and even unskilled workers. The contribution of this sector to India's GDP increased from 1.2 percent in FY1998 to a peak of 9.5 percent in FY2015, falling to 7.4 percent in FY2022 (Statista 2023). The sector ranked second in terms of foreign direct investment (FDI) inflows amounting to USD 48.67 billion between April 2020 and December 2022 out of the total inward FDI flow of USD 222 billion during this period (DPITIT, 2022). The IT and BPM (Business Process Management) industry together employs more than 4.85 million workers at the end of FY2022 (Statista, 2022).

The most important competitive advantage of this sector in India, which stoked its rapid growth since the early 1990s, was the low cost of human capital (initially engineers) compared to their foreign competitors. The efficiency of managerial inputs (in terms of strategy, resource allocation, finance, and so on) is also important, but labour cost arbitrage continues to be the major driver even in recent times (Sabnavis & Unwalla, 2020). Given the importance of this sector to India, the question arises about the economic and financial sustainability of this sector. For any industry, the main goal is either to sustain an achieved level of efficiency or to enhance the efficiency to an optimal level. Against this backdrop, the main objective of this paper is to assess the productive efficiency of this sector. To analyse this sector's performance and evaluate its efficiency, we use Data Envelopment Analysis (DEA) which is a non-parametric method based on repeated solutions of linear programming problem (LPP), free of any assumption regarding the probability distribution of the model variables underestimation. Besides, this technique is capable of handling multiple inputs and outputs. Specifically, we use a variant of DEA called additive-DEA (Cooper et al. 2007), henceforth mentioned as ADD-DEA in this paper, which is invariant to data translation, in addition to being non-radial and non-oriented.

The rest of the paper is structured as follows. The next section presents a review of the literature, followed by a section describing the data, variables, and methodology, a section discussing the results, and finally, the conclusion.

2. Literature Review

In this section, the paper analyses two strands of literature, one focusing on the relevant theoretical aspects of the ADD-DEA methodology (along with the method for selection of proxy input and output variables using the Balanced Score Card or BSC framework) and the other on empirical literature using DEA techniques in the context of the Indian IT & ITeS industry.

DEA is a non-parametric technique used to measure the productivity of each of the firms in a chosen sample. Issues with parametric methods for multi-product and multi-input firms have been succinctly explained in Melitz (2000). Charnes et al. (1978) first proposed the DEA technique (hereafter the CCR model) based on Farrell (1957). This original DEA model maximises the output(s) for a given set of inputs, assuming constant returns to scale (CRS), and is the primary Input-Oriented (IO) CCR model. The model assumes that no positive or negative economies of scale exist (i.e., a small unit should be able to operate as efficiently as a large one). However, Banker et al. (1984) (henceforth BCC model) removed the restriction of CRS by allowing for variable returns to scale (VRS), thereby enabling inference about the returns to scale of each sample firm.

Following the works of Charnes et al. (1978) and Banker et al. (1984), prolific literature on DEA spawned since the 1980s, spanning modifications or extensions of theoretical models, economic interpretations of the models, and empirical applications; for details, refer to Cooper et al. (2007) and Emrouznejad & Yang (2018).

Despite the development of several variants in the DEA literature, the basis for most of these models is still the CCR and BCC models, particularly in empirical applications. However, both CCR and BCC models suffer from a few limitations. First, both these models can either be input-oriented (attempting to minimise the use of inputs while holding the outputs constant) or output-oriented (attempting to maximise outputs while holding the inputs constant). Second, both these models are radial in that sense that they assume that inputs (outputs) are used in fixed proportions to each other – so that the input reductions (output-expansions) by management of inefficient firms may be achieved while keeping the respective proportions unchanged. This, in our opinion, amounts to unchanging technology (substitutions among inputs or outputs not allowed), and hence unsuitable for application in the context of an industry characterised by rapidly changing technology like the IT & ITeS industry. The third limitation of these (and several other DEA) models is the inability to handle the presence of negative values in the input/output variables. Since linear programming problems (LPPs) with negative values cannot be solved in general, variables with negative values need to be translated to make the value of each element of every variable (input and output) at least non-zero through translation. For example, if profits or profit margins are used as an output, data translation becomes inevitable since some firms or decision-making units (DMUs) may incur loss in some of the years, necessitating data translation (adding a positive quantity to all values of the variable in question to make entire sample non-negative). Another limitation is that of data transformation (not just data translation) is the requirement to handle widely diverging values of inputs (outputs) across sample DMUs when non-radial models are used, which report efficiencies or inefficiencies in terms of absolute values or quantities of inputs (outputs) used, thereby requiring scaling of input (output) values. However, there are some DEA models that are translation-invariant, and some are scale-invariant, but no DEA model is invariant under transformation (simultaneous translation and scaling) in the primal form of the models.

However, there is a non-oriented and non-radial class of Additive DEA models (Cooper et al. 2007) that simultaneously computes input excesses and output shortfalls (both termed as slacks) and does not assume inputs (outputs) should change while keeping their relative weight constant (as in radial models). There are a few variants of ADD-DEA models (like weighted, un-weighted, unit-free etc.), but due to data translation, the un-weighted (or equal-weight) ADD-DEA model is preferred (Cooper et al. 2007), which is used in this study. The use of the ADD-DEA model in this paper is necessitated by two interrelated factors. First, unlike the majority of empirical research using DEA models, we attempt to select proxies for inputs and outputs using the Balance Score Card (BSC) framework rather than selecting the proxies arbitrarily or by referring to previous literature that resorted to similar arbitrary selection of proxy variables. Second, the BSC framework leads us to select certain variables (like measures of profitability) that may become negative for some of the firm years in the sample where data translation is necessary. DEA has been used to measure whether the observed inefficiency is due to managerial underperformance or choice of inappropriate scale size, like the study done by Kumar and Arora (2012) and Kumar and Gulati (2019).

Regarding the literature focusing on the efficiency and productivity of the Indian IT & ITeS sector using the DEA framework, we have found only a handful of papers. Mathur (2007) uses an input-oriented DEA to compute technical efficiencies for a sample of 92 firms from this sector for the financial year 2005-06 with two output variables (sales and net exports) and three input variables (number of employees, years in business, and total costs). The study found that the industry average of technical efficiency score is 0.69 (a score of 1 means most efficient in the sample). The study reports that technical efficiency is positively influenced by size (sales as proxy) and net exports, and negatively influenced by total costs. Further, size has a positive, and total costs have a negative influence on net exports. The same study (Mathur, 2007) also computes and decomposes total factor productivity (TFP) change for a sample of 32 firms between 1996 and 2006 into technical change and efficiency change and reports that the TFP increased by more than 27% on average for the sector between these two years, with a few firms exhibiting stellar performance in this regard. While for the sample average, the TFP change is roughly equally distributed among efficiency change (or catching up with the frontier technology effect) and technical change or innovations (or movement of the frontier itself), for the super-achievers, TFP changes are mostly due to movements of the frontier rather than catching up.

Sahoo & Nauriyal (2013) used input-oriented CCR and BCC models and Malmquist Productivity Index (MPI) for a sample of 72 firms during 1999-2008 to estimate TFP and its constituents (technical, scale, and allocative efficiency change). The results show that pure technical efficiency (PTE) improved for the average across the sample in four of the eight years and decelerated in the other four years but improved on an overall basis (entire study period). Authors attribute this to the advancement in hardware and software technology leading to higher efficiency of the firms in converting inputs into outputs, whatever the RTS. However, the study found evidence of decelerated overall technical efficiency (OTE) and evidence of deteriorating scale efficiency (SE)[1]. Deteriorating scale efficiency over the entire study period brings down the OTE score, offsetting some of the positive effects of PTE on OTE. Authors conjecture that this is probably due to the presence of a large number of small firms (along with a few large firms), with the former failing to scale up in size and reap efficiency benefits due to scale. Overall, the authors report that the majority of the firms are inefficient, probably because the pressure of catering to the export market takes away managerial attention from efficiency improvement.

Das (2017), using used the DEA-based Malmquist Productivity Index for 70 Indian IT firms for the period 2004 – 2014, which shows that there has been improvement in total factor productivity (TFP) in the sample firms, led by technological progress, including innovations, and that the inefficient firms have been lacking in managerial efficiency. Results show that export intensity, salaries/wages intensity, and age positively influence TFP growth, but firm size has an insignificant influence. The paper also finds that the productivity of the sector has deteriorated after the US GFC. Das & Datta (2017) used varying numbers of firms, starting from a minimum of 11 firms in 2000 and a maximum of 72 firms in 2012 (sample period is from 2000 to 2014), showing that the average efficiency score is less than one across all measures of efficiency and that inefficiency measured by OTE is mainly due to PTE (or managerial inefficiency), rather than due to SE measure of inefficiency (inappropriate scale size). The results further reveal that firm size, market concentration, net exports, and profit rate have a positive and significant impact on efficiency. Bhat & Kaur (2019), using a sample of 100 firms to measure the efficiency and productivity (TFP) of the Indian IT & ITeS sector between 2006 and 2005, report that the OTE of most firms is led by the SE rather than PTE, which is not in line with the other works mentioned above. While the number of efficient firms (by OTE measure) increased over the years, the sample firms have performed poorly with respect to TFP change over the sample period, with productivity growth being positive in five of the eleven years.

From the above-reviewed studies, which are focused on the productive efficiency of IT & ITeS in the Indian sector, apart from the limitations of DEA models outlined

[1] BCC measure of technical efficiency is known as PTE, which represents managerial efficiency. CCR measure of technical efficiency is known as OTE, which takes care of managerial efficiency as well as scale efficiency. SE is the efficiency arising out of the scale of a firm and is defined as the ratio of OTE to PTE.

earlier, we also found evidence of an inappropriate definition of variables[2]. It is pertinent to mention here that none of these studies considered any specific method to identify the input-output parameters to measure efficiency.

Our study tries to fill this gap by addressing these issues. To overcome the limitations of radial DEA models (CRR & BCC), we use the ADD-DEA model; and for identifying variables (efficiency parameters) for this study, we use an integrated BSC[3]-DEA approach (Asosheh et al., 2010), (Kadarova et al., 2015).

3. Methodology and Data

The additive model that considers the input excess and output shortfall simultaneously is given as.

$$(ADD_o)\ \max_{\lambda,s^-,s^+} z = es^- + es^+$$

$$Subject\ to$$

$$\begin{gathered} \mathrm{X}\lambda + s^- = \mathrm{x_o} \\ \mathrm{Y}\lambda - s^+ = \mathrm{y_o} \\ e\lambda = 1 \\ \lambda \geq 0, \qquad s^- \geq 0, \qquad s^- \geq 0 \end{gathered}$$

Where X is the vector of m inputs, Y is the vector of n outputs, x0 and y0 indicate the particular DMU under evaluation, e denotes a row vector in which all elements are equal to 1, s^- and s+ denotes input and output slacks respectively.

In the additive model, the efficiency evaluation does not depend on the origin of the coordinate system. If there is a change in the origin of any input or output, the optimal solution to the new problem in its primal form will remain the same as that of the original problem. This consistency is called the Translation Invariance of the ADD-DEA model and helps to deal with negative data. For the purpose of variable selection, the four perspectives considered by BSC are (1) financial, (2) customer, (3) internal business processes, and (4) innovation (learning and growth). These help to provide a comprehensive view of the business performance under the BSC framework.

The financial perspective is reflected through the proxy variable total liabilities as an input variable. This begs an explanation. High rates of growth achieved by a majority of firms in this sector have been traditionally financed by the public equity markets since the early 1990s (Murthy, 2011). The major reasons were the liberalisation of the process of issuing equity to the public and the reluctance of commercial banks

[2] Papers like Mathur (2007) and Sahoo & Nauriyal (2013) have considered age as an input parameter, which violates the DEA assumption for input parameters for reduction.

[3] The Balanced Scorecard (BSC) is a strategic tool that uses various perspectives, such as financial, customer, internal business processes, innovation, and learning and growth, to identify an organization's key performance indicators (Kaplan & Norton, 1996).

to lend to these firms that did not possess assets that could be held as collateral (Mehta, 2022). However, over the period, these firms (a vast majority of them listed) earned enormous amounts of profit but distributed very little to the shareholders by way of dividends and equity buyback in any significant measure, leading to ever-increasing retained earnings. Total liability for the sample average consists overwhelmingly of the owners' equity. Total liability is an input variable that captures the financial capital deployed by the firm to create assets that produce the services.

The customer perspective tries to answer the question, "How do customers value the organisation?" Higher revenue indicates a higher value of the organisation as perceived by customers. Edvardsson et al. (2000) found that customer satisfaction and loyalty lead to higher revenue growth in Swedish service firms. Babakus et al. (2004) showed for retail stores, better service quality leads to higher revenue growth. As such, revenue is considered the output parameter of the customer perspective. While revenue as an output variable captures customer satisfaction at the delivery stage (after the customers have been acquired), firms need to invest in acquiring new customers and retaining existing customers. For this purpose, firms need to invest resources in marketing efforts, including sales promotion. Selling General & Administrative Expenditure (SGAE) is the sum of all direct and indirect selling expenses (including advertising expenses), general and administrative payments (including rental costs), sales training, travel, promotional materials, marketing and advertising, content creation, website development and maintenance, social media marketing, trade show participation, and market research. The customer perspective of BSC emphasises customer satisfaction, loyalty, and value creation measures. SGAE expenses have a significant influence on customer-related metrics. Efficient allocation of SGAE expenses contributes to activities that enhance customer satisfaction, improve service quality, enable effective marketing efforts, and support customer-centric initiatives. SGAE is thus the proxy variable on the input side, capturing customer satisfaction. Evidence shows that lower SGAE represents efficiency in cost management, and intentional increase significantly enhances future earnings (Baumgarten et al. 2010).

The internal business process perspective is reflected through two proxy variables: earnings before interest, tax, depreciation, and amortisation (EBITDA) as an output variable and the cost of goods and services sold (CoGSS) as an input variable. The internal business process perspective thrives on higher process efficiency, which means a lower operational cost. Improvement in process efficiency by implementing tools like Six Sigma improves the bottom line and reduces the cost of goods and services sold (CoGSS) (Harry, 1998), (Bisgaard & Freiesleben, 2004), (Mahanti & Antony, 2009). CoGSS is the direct cost attributable to the production of goods and services sold by a company and is considered an input variable capturing internal business processes. The single most important constituent of CoGSS for our sample of firms is the expense of wages and salaries. We do not have the company-wise number of employees over the years. So, the expense on employees as part of COGSS is used as the proxy.

Earnings before interest, tax, depreciation, and amortisation (EBITDA), a measure of operating profit not influenced by factors like the intensity of assets, capital structure, and direct taxes, is the proxy variable on the output side to reflect internal business process perspective. Process efficiency (and cost minimisation) without jeopardising customer satisfaction should be reflected in this measure of profit. Besides, use of EBITDA as an output variable in DEA analyses is not uncommon in the literature (Oberholzer, 2014).

The learning and growth perspective attempts to achieve sustainability in an organisation's ability to change and improve. Research and development expenditure (R&DE) is considered as an input to achieve this sustainability. Evidence indicates that R&DE positively influences the quality of patents, which drives future performance for innovative firms (Pandit et al., 2011), revenue growth (Öztürk & Zeren, 2015), and output growth (Binh & Tung, 2020). Unfortunately, due to the unavailability of data on R&DE for most of the firms in our sample, we could not include the learning and growth perspective of BSC in this paper. Another alternative variable is intangible assets (e.g., brands, goodwill, intellectual property), but the non-availability of data on this variable also forces us to ignore the learning and growth perspective.

The BSC framework adds an important qualitative aspect to the variable selection process for the ADD-DEA model that requires some clarifications. To begin with, of the four BSC perspectives, we use TL as the input variable for the financial perspective (and none on the output side), SGAE as the input variable and revenue as the output variable for the customer perspective, and CoGSS as the input variable and EBITDA as the output variable for the internal business process perspective. Non-availability of data on variables potentially capable of capturing learning and growth perspective forces us to ignore this aspect. Given this, now let us explain how the BSC framework helps in variable selection. For example, CoGSS and SGAE could have been included on the input side of the financial perspective (in addition to TL) and revenue and/or a measure of profit could have been included on the output side of the same perspective. However, it is the BSC framework coupled with the structural characteristics of the industry that leads us to select SGAE (customer service) as the input variable and revenue as the output variable to capture the customer perspective. The choice of CoGSS (of which the dominant constituent is wages and salaries) as the input variable and EBITDA (a measure of operational profit not influenced by capital structure, tax structure, and asset intensity) as the output variable for the internal business process is indicated by the BSC framework.

The data on input and output variables are collected from the Prowess Database of the Centre for Monitoring the Indian Economy (CMIE). The sample period is from FY2005-06 to FY2018-19 (henceforth mentioned as 2006 – 2019). The choice of the initial year was made to begin before the global financial crisis, while the selection of the final year was made to preclude any possible influence of the COVID-19 pandemic. We begin with all IT & ITeS firms in the Prowess database, but information on the selected input (TL, SGAE, CoGSS) and output (revenue and EBITDA) variables for each of the 14 years under study are available for a set of 74 firms.

After obtaining the results from the ADD-DEA model, we attempted to analyse the efficiency scores using a regression framework (generalised two-stage least squares (G2SLS). Appropriate explanatory variables (the dependent variable being the efficiency score in the percentage of the original value for each input and output at a time) were chosen following the empirical literature. The model we estimate is as follows.

$$IE_{jit} = \alpha + \beta_1 A_{it} + \beta_2 S_{it} + \beta_3 O_{it} + \beta_4 E_{it} + \beta_5 I_{it} + \beta_6 B_{it} + \beta_7 M_{it} + u_{it} + \varepsilon_{it}$$

IE_{it} = in-efficiency of firm i at time t
A_{it} = age of firm i at time t
S_{it} = size of firm i at time t
O_{it} = outward orientation of firm i at time t
E_{it} = exchange rate at time t (same for all firms in a year)
I_{it} = industry specialisation of firm i at time t
B_{it} = business specialisation of firm i at time t
M_{it} = market (geography) specialisation of firm i at time
$\mathrm{t}u_{it}$ and ε_{it} are between $-$ entity error and within $-$ entity error terms

i = 1, … , 74 and t = 1, …, 14; and the model is estimated individually for slacks of each input and output separately. The firms in our sample differ in different characteristics like business type (IT consultancy; Software development; Internet Services, Infrastructure, network, and hardware supply; and maintenance, data processing, and outsourced services), catering to different industries (Finance; Government; Industrial and Consumer Discretionary client; and Communication clients) and market focus (catering to foreign and/or domestic market). We collect further information from the Bloomberg database and websites of the respective firms to identify the business type, industry specialisation, and market focus for each of them.

Under industry specialisation (sectors catered to by these firms), we find that 56 of the 74 firms cater to all the sectors, while others cater to anything falling short of all the sectors. Thus, the industry specialisation dummy variable takes the value of 0 for those 56 firms and 1 for others. In the case of business type, since most firms are into several verticals and none into all verticals, we classify the business type by the most important vertical according to the firm and as specified in the Bloomberg database. Here, the business type for 49 out of 74 firms (66%) is “IT consulting”, and this includes the top five firms of the sample and the industry (TCS, Infosys, Wipro, Tech Mahindra, and HCL Tech). Business type dummy variable is assigned the value of 0 for this type, and 1 for all others. The market focus dummy variable is constructed according to whether a firm caters to the clients in the domestic economy alone or domestic as well as foreign markets. Out of 74 firms, 68 (92%)

cater to the global markets, and only 6 cater to the domestic economy, and the market focus dummy variable takes the value 0 for those 68 firms and 1 for the rest.

Despite the small variations across firms regarding industry specialisation, business type, and market focus, all these firms can be considered homogeneous, and a single efficiency frontier can still be drawn for the following reasons. First, while the relatively larger firms (by revenue) are present in a majority of verticals or business types and cater to clients from all sectors and geographies, smaller ones usually focus on a few of those. However, there is no restriction on a firm entering or exiting a particular business type (or client or market) from one year to another. Second, the basic technology (hardware, software) and the inputs (workforce and managerial efforts and inputs) are the same for all the firms. Third, DEA measures the efficiency of Decision Making Units (DMUs) that pursue the same goals and objectives (Kocisova et al. 2018) (in this case, maximising total revenue and EBITDA, and minimising COGS, SGAE, and supposedly total liability) and use similar inputs, the firms may be considered homogeneous. Finally, the unit of measurement for the input and output variables is the same (millions of INR) across all the firms, a condition required for homogeneity of firms (Khezrimotlagh & Chen, 2018).

4. Results

The ADD-DEA model produces inefficiencies in terms of input excess or output shortfalls in absolute terms, and a firm is efficient when the slacks of each input and output are zero. Since the size of firms (by revenue, assets, EBITDA) in the sample varies substantially, we have converted the absolute input and output slacks of a firm-year into the percentage of the respective input used (output produced) by dividing the slacks by the actual value of corresponding input used (output produced) in that specific year. The results are reported in Table 1.

Figure 1 shows that the average input slacks are much higher than the average output slacks. This is consistent with the fact that Indian service providers face constraints on the output side - clients monitor deliverables very strictly. However, these firms do not face any constraints on the input side. On the input side, inefficiencies are pronounced for SGAE and TL but relatively far less for CoGSS (which includes wages and salaries). Inter-temporal variations in percentage input excesses with respect to CoGSS and SGAE for inefficient firms may partly be due to the structural characteristics of the industry and partly due to changes in external demand conditions and factor prices (apart from firm-specific inefficiencies). The industry needs to maintain a certain percentage of employees on the bench (i.e., not being utilised in any project or work) for various reasons like fresh recruits on training, employees from a completed contract or project waiting for redeployment in another contract, and in anticipation of winning new contracts in near future, and attrition.

Table 1. Input and Output Slacks as % of Total

Year	Excess COGSS	Excess SGAE	Excess Total Liability	Shortfall in Revenue	Shortfall in EBITDA
2006	5.8%	35.5%	33.3%	17.6%	17.2%
2007	8.2%	46.2%	40.0%	1.6%	25.9%
2008	10.3%	18.1%	35.6%	8.4%	7.0%
2009	16.4%	40.3%	37.6%	4.4%	9.7%
2010	18.0%	60.5%	40.2%	0.5%	20.6%
2011	11.5%	39.1%	25.4%	1.4%	26.8%
2012	13.2%	40.0%	29.8%	4.0%	15.6%
2013	17.8%	44.8%	33.4%	6.8%	17.5%
2014	10.6%	45.8%	33.3%	4.1%	14.6%
2015	7.9%	39.4%	36.7%	1.0%	13.4%
2016	7.9%	44.9%	30.0%	2.3%	16.7%
2017	10.1%	47.2%	30.3%	6.2%	16.0%
2018	19.3%	34.1%	35.4%	0.05%	37.5%
2019	11.9%	4.3%	35.3%	0.3%	32.4%

Source: Authors' calculation.

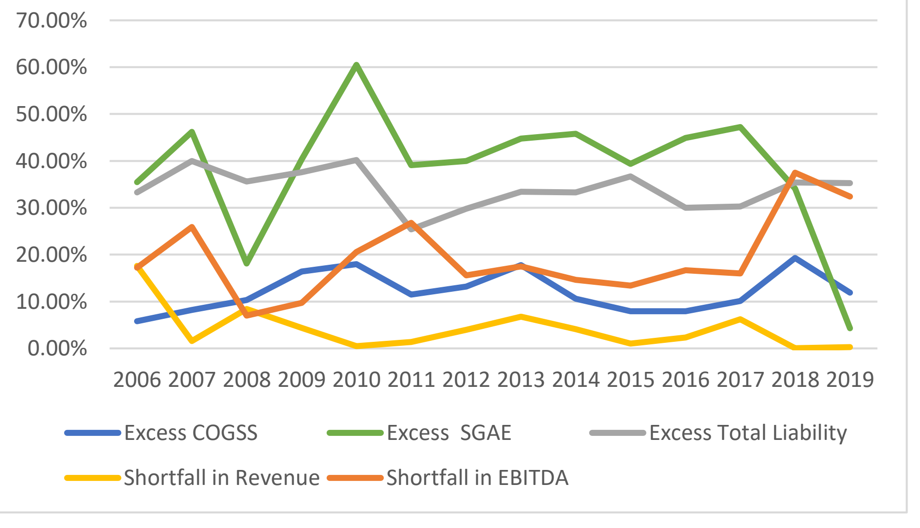

Figure 1. Input and Output Slacks as % of Total
Source: Authors' calculation

For example, according to the Annual Report 2018-19 of Infosys, employee utilisation is defined as "... the proportion of total billed person months to total available person months, excluding sales, administrative and support personnel." It also furnishes that the employee utilisation rate is 80.1%, including trainees, and 84.5% excluding trainees in 2019 (81.8% and 85.2% in 2018) and states that "revenues and gross profits are also affected by employee utilisation rates." This is simply because revenues are earned on the basis of billing rate per utilised employee and are realised subject to fulfilment of specified contractual obligations. Annual Report 2018-19 of TCS furnishes that the attrition rate faced by the company in FY19 is 11.3% (13.8% in FY15, 14.7% in FY16, 10.5% in FY17, 11.0% in FY18), and claims that it is the lowest in the industry. It states: "Lower attrition is always a good thing because it reduces disruptions caused by employee churn and results in better outcomes for customers. This is even more significant now because retaining contextual knowledge within the team is central to our ability to design those transformational solutions and partner with our customers in ongoing programs." TCS is known for the lowest attrition rate in the industry.

Wages and salaries dominate CoGSS, whereas SGAE consists of expenses on marketing and promotional activities, sales training, travel, advertising campaigns, digital marketing, content creation, website development and maintenance, social media marketing, trade show participation, market research, and so on. Given the above background, the percentage inefficiency in CoGSS is relatively less than SGAE simply because greater relative inefficiency in CoGSS drastically reduces profitability than in SGAE, which accounts for a lower proportion of total expenses of all firms. Besides, the amount of expenditure on SGAE is usually determined by the top management and faces no external constraints and is to some extent discretionary. This explains the larger inefficiency of SGAE than CoGSS as well as greater inter-temporal variation in SGAE inefficiency. The discretionary nature of SGAE is corroborated by a sudden drop in SGAE inefficiency in 2008 associated with the GFC. The CoGSS inefficiency was the lowest in the first three years, in line with the GFC originating in the US housing finance market from 2006, and began to increase from 2009 when firms could get new business from clients in the foreign markets struggling to cut costs by outsourcing more in-house activities to the Indian IT & ITeS firms. However, the trend changed after 2015 (2016) for efficient (inefficient) firms, but that we take up at a later stage.

On the output side, shortfall in revenue is far lower than that for EBITDA, which is again consistent with revenue depending on fulfilment of contractual obligations with the client. However, shortfall in EBITDA varied over the years and was determined substantially by external economic conditions like exchange rate and demand conditions in developed markets. Surprisingly, this shortfall was reduced substantially in 2008 and 2009, the two years when this sector in India was negatively affected by the global financial crisis – most likely because firms were forced to adopt cost-cutting measures in the face of a crisis.

One interesting aspect is the consistent input excess in the case of total liabilities, which is almost cent percent equity. This implies that inefficient firms consistently used far more equity capital than is required to produce the same outputs. One plausible explanation is that almost all these firms have been financed by public equity markets coupled with the fact that their USD revenues converted to INR fired by continuous currency depreciation caused consistently high growth in earnings, leading to high market valuations. It should be noted that total liability (equity) here is the paid-up equity capital plus reserves and surplus, including retained profits (jointly known as owners' equity).

In line with earlier empirical evidence, we find that the number of efficient firms is very low, varying between a minimum of 13 (in 2017) and a maximum of 20 (in 2016) out of 74. Efficiency scores show that eighteen firms remained inefficient in all the periods, and sixteen firms could achieve efficiency in just one of the fourteen years. On the other hand, only two firms remained efficient in all the periods, one firm remained efficient in eleven periods and three firms remained efficient in ten periods. Overall, sixty-three firms remained inefficient in seven or fewer years, and eleven firms remained efficient in eight or more years.

Efficiency or inefficiency manifests itself in the growth and profitability of the sector. While the average efficient firm was only 3.5 times as large by revenue in 2006, it reached 6.8 times by 2019. The increase in relative size by EBITDA is sharper: from 3.9 times (2006) to 9.7 times (2019). Measured by return on equity (ROE), efficient firms remained far more profitable than inefficient firms throughout the sample period (Table 2 and Figure 2). In other words, efficient firms have recorded higher and growing average revenue, and average EBITDA and reported much higher and consistent average return on equity (ROE) than inefficient firms.

Table 2. Efficiency, Differential Growth, and Profitability

Year	Number of firms		Average Revenue (Efficient/ In-efficient)	Average EBITDA (Efficient/ In-efficient)	Average ROE (%) for Efficient Firms	Average ROE (%) for In-efficient Firms
	Efficient	Inefficient				
2006	20	54	3.5	3.9	28.6%	-0.3%
2007	16	58	4.2	5.9	20.2%	9.9%
2008	19	55	3.5	4.1	20.5%	10.6%
2009	18	56	3.9	4.8	24.8%	5.8%
2010	19	55	3.9	5.2	23.1%	-18.5%
2011	17	57	1.8	2.4	18.4%	-12.9%
2012	15	59	2.9	3.4	21.2%	-9.9%
2013	16	58	3.4	4.3	37.1%	12.9%
2014	18	56	2.4	2.9	25.0%	12.8%
2015	18	56	2.7	3.2	19.1%	-12.3%
2016	20	54	2.4	2.9	21.8%	9.3%
2017	13	61	3.5	4.4	22.5%	3.1%
2018	16	58	3.2	4.6	22.3%	-4.0%
2019	18	56	6.8	9.7	60.5%	8.6%

Source: Authors' calculation.

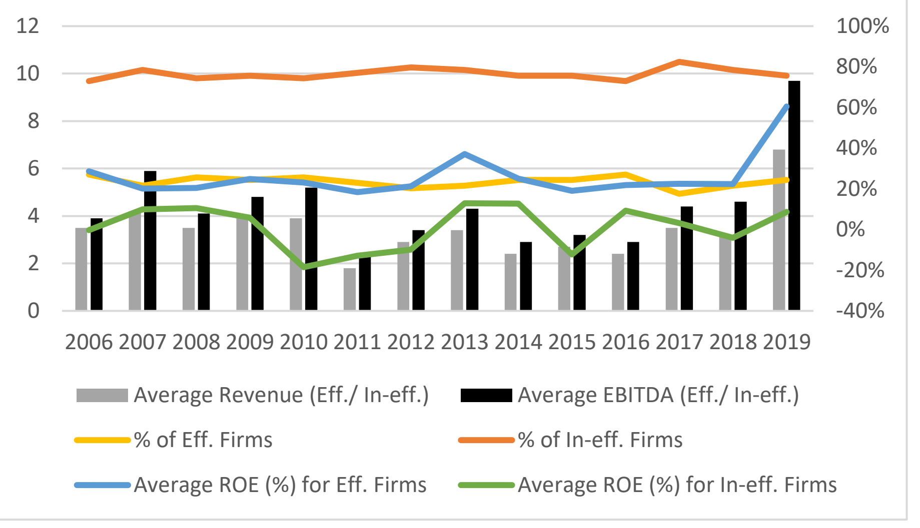

Figure 2. Efficiency, Differential Growth and Profitability

Source: Authors' calculation

The export of services as a percent of total revenue is an important performance indicator for this sector. However, apparently, there is not much difference between efficient and inefficient firms in this respect (Table 3 and Figure 3). This implies that being inefficient does not hinder the firms from catering to their foreign clients. For example, inefficient firms earned a greater proportion of their revenues from exports between 2012 and 2017. On a closer examination of inter-temporal variations in efficiency of each firm, we notice that during 2012-17, a few very large firms (Infosys Ltd., Capgemini Technology Services India Ltd., Mphasis Ltd., Tech Mahindra Ltd., Oracle Financial Services Software Ltd. Larsen & Toubro Infotech Ltd., and HCL Technologies Ltd.) which predominantly cater to foreign markets turned inefficient for some or all of the years. By average revenue during 2012-17, each of these firms belonged to the top ten size group. Even then, the total revenue earned by the efficient firms was less than that of inefficient ones every year from 2012 to 2017.

However, there has been a sharp decline in this proportion in the last few years of the sample for all firms (from 2016 for efficient firms and 2017 for inefficient firms). A plausible explanation for this trend may be based on a few factors. First, foreign clients of Indian IT firms have increasingly opened wholly owned subsidiaries in India. At the time of renewal of the contract by the foreign client with an Indian service provider, the former is now increasingly making the Indian subsidiary sign the contract with the latter. Proximity of service production, as achieved, facilitates better communication, collaboration, and alignment with the client's business strategies, leading to greater operational efficiency. Indian service providers also benefit from lower communication and travel costs of coordination with their clients, which helps them to optimise costs.

Table 3. Export of Services and Goods as % of Total Revenue

Year	Export of Services % of total revenue		Export of Goods % of total revenue	
	Efficient	Inefficient	Efficient	Inefficient
2006	62.84%	55.22%	0.09%	1.15%
2007	72.93%	60.71%	0.19%	0.76%
2008	70.52%	64.09%	0.29%	1.02%
2009	83.00%	76.61%	0.00%	1.30%
2010	74.02%	67.68%	0.01%	0.83%
2011	66.55%	66.30%	0.01%	2.59%
2012	66.99%	73.93%	0.00%	2.27%
2013	61.98%	74.84%	0.16%	1.29%
2014	79.11%	82.76%	0.02%	0.46%
2015	77.97%	82.82%	0.00%	0.24%
2016	9.86%	85.75%	0.01%	0.08%
2017	2.08%	7.30%	0.00%	0.16%
2018	6.89%	1.00%	0.01%	0.07%
2019	4.21%	3.23%	0.00%	0.02%

Source: Authors' calculation

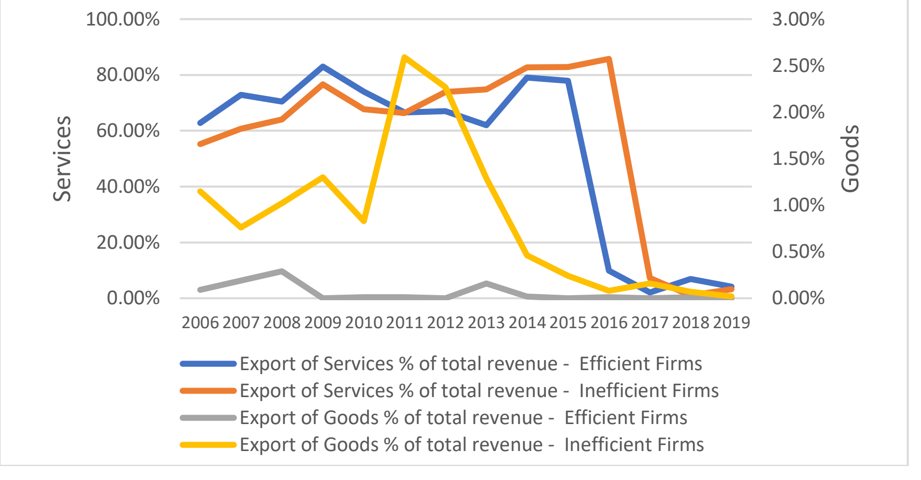

Figure 3. Export of Services and Goods as % of Total Revenue for Efficient and Inefficient Firms

Source: Authors' calculation

Second, a foreign client (of an Indian service provider), which is currently not catering to the Indian market, has the incentive to open a subsidiary with the hope that it will acquire knowledge about the local market and eventually begin to offer its product/services to the growing Indian market. Third, working with the Indian subsidiary helps both the Indian IT firms and the foreign clients to comply with local regulations, legal requirements, and taxation policies. The services provided align with Indian laws and regulations, reducing any potential compliance-related risks.

Fourth, when Indian IT firms do business with the Indian subsidiary of their foreign clients instead of the corporate office outside India, there can be certain tax advantages or disadvantages. It is important to note that tax implications can vary based on specific circumstances, tax laws, and bilateral tax treaties between countries. Tax holidays, reduced tax rates, or other tax incentives may exist for companies operating in specific industries or regions within India. If the Indian subsidiary is considered an Indian tax resident, certain payments made by the Indian subsidiary to the Indian IT firm may be subject to lower or no withholding tax, which can result in improved cash flow for the IT firm. By transacting with the Indian subsidiary of the foreign client, Indian IT firms can establish transfer pricing policies in compliance with Indian tax regulations, which allows them to determine arm's length pricing for intra-group transactions and mitigate potential transfer pricing disputes. Indian IT firms must consult with tax professionals with expertise in international taxation and a deep understanding of the specific circumstances and applicable tax laws.

All these possibly can explain the drastic fall in foreign exchange earnings as a percentage of total revenue by the Indian service providers as they booked more of the revenues in INR and less in USD in their audited accounting statements. These issues may also explain the substantial reduction in foreign expenditure on travel as a percentage of total revenue for all firms (Table 4 and Figure 4). SGAE is one of the input variables, of which a constituent is foreign exchange expenditure on travel as a percentage of total revenue. This ratio is far higher for inefficient firms than for efficient ones (except in the last three years), implying that inefficient firms ended up spending more foreign exchange resources for servicing existing clients as well as for winning new clients compared to efficient firms. This is probably due to the far larger size of the average efficient firms.

Table 4. Foreign Exchange spent on travel as % of Total Revenue

Year	Efficient firms	Inefficient firms
2006	1.66%	10.56%
2007	1.77%	10.66%
2008	1.66%	10.97%
2009	1.17%	13.65%
2010	1.18%	10.80%
2011	0.37%	7.63%
2012	0.39%	7.69%
2013	0.28%	8.64%
2014	0.44%	1.89%
2015	0.45%	8.78%
2016	0.10%	8.69%
2017	0.00%	0.10%
2018	0.05%	0.02%
2019	0.02%	0.02%

Source: Authors' calculation

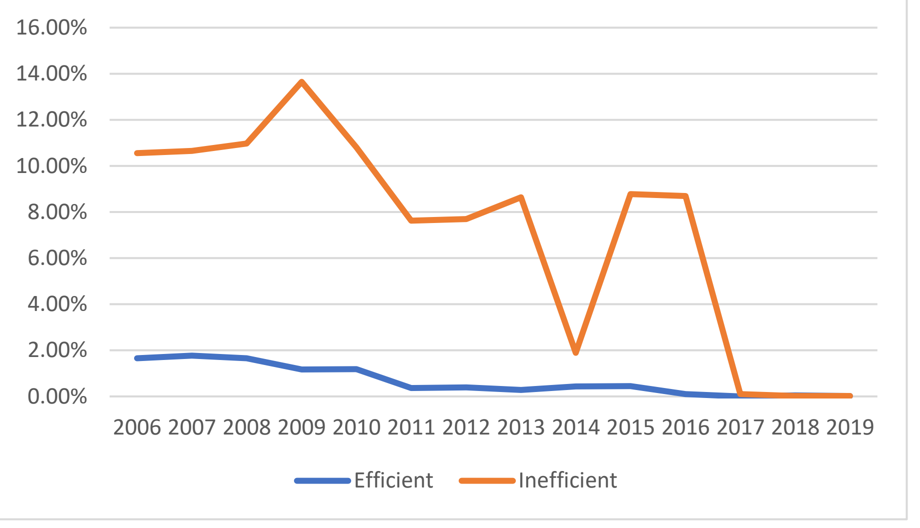

Figure 4. Foreign Exchange spent on travel as % of Total Revenue for Efficient and Inefficient firms

Source: Authors' calculation

However, this figure has come down for all firms (Table 4 and Figure 4). This is certainly due to changes in technologies (hardware and software) and increasing speed and bandwidth of the internet, reducing the need for foreign travel to deliver services at client locations (on-site).

Firms invest their surplus funds into short-term and long-term financial assets, and the IT & ITeS firms are no exception. Their investments in equity shares, bonds, and mutual funds (EBMF) plus cash and bank balances (CBB) as a percentage of total assets (or total liabilities) remained just below 50 percent for inefficient firms except for 2014 and at a consistently higher level (except for 2014 and 2015) for the efficient firms (Table 5 and Figure 5). Given that total liability (TL) is an input in the ADD-DEA model, and financial investments mostly reflect retained profits (part of TL), a high degree of inefficiency in the use of TL as shown by the ADD-DEA model is not surprising. Besides, the efficient firms held more percentages of total assets in CBB (which are mostly short-term investments) than in EBMF (mostly long-term investments). However, the inefficient firms did the opposite during 2006 to 2010 and in 2019. In audited financial statements, usually, investments in EBMF are stated in market value terms, which fluctuate from year to year in line with the movement of equity markets and benchmark interest rates, while CBB is stated in actual or face value terms. The amount of investments in CBB is determined more by firm-specific factors and managerial decisions (in response to probable changes in the business environment and risks) and less in the case of investment in EBMF. Maintaining an adequate cash and bank balance is crucial for day-to-day operational needs, working capital management, and unforeseen contingencies.

Table 5. Investment as % of total assets

Year	Investments in equity shares, bonds, and mutual funds as % of total assets		Cash & Bank Balance as % of total assets		Total Financial Investment as % of total assets	
	Efficient	Inefficient	Efficient	Inefficient	Efficient	Inefficient
2006	20.0%	18.8%	31.3%	11.3%	51.3%	30.1%
2007	17.5%	23.9%	34.0%	12.3%	51.5%	36.2%
2008	19.4%	19.3%	30.6%	13.1%	49.9%	32.5%
2009	21.7%	21.6%	25.9%	16.1%	47.6%	37.8%
2010	23.6%	24.0%	33.9%	13.6%	57.5%	37.5%
2011	24.1%	19.8%	25.0%	22.7%	49.0%	42.5%
2012	21.7%	12.8%	22.5%	26.2%	44.2%	39.0%
2013	21.2%	11.2%	23.3%	27.4%	44.5%	38.6%
2014	13.9%	21.7%	20.5%	27.4%	34.4%	49.1%
2015	9.9%	24.2%	20.3%	27.2%	30.1%	51.4%
2016	23.7%	16.1%	24.9%	23.0%	48.6%	39.1%
2017	35.7%	9.1%	36.6%	14.0%	72.2%	23.1%
2018	33.3%	7.9%	33.7%	12.0%	67.0%	19.9%
2019	25.1%	17.6%	36.3%	11.1%	61.4%	28.8%

Source: Authors' calculation

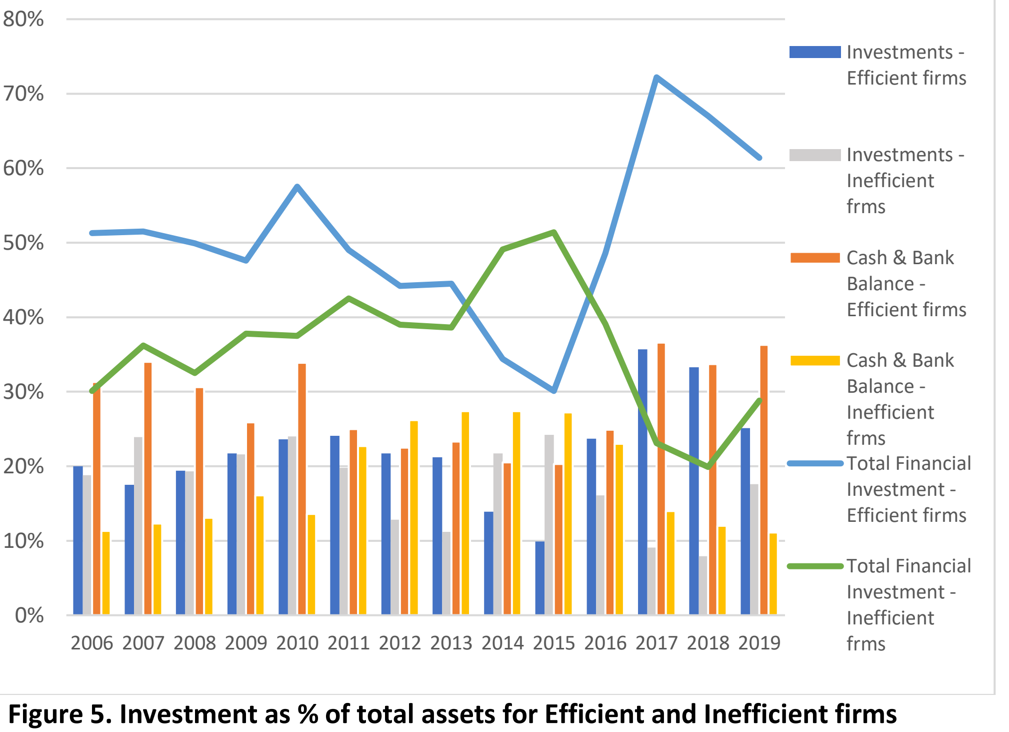

Figure 5. Investment as % of total assets for Efficient and Inefficient firms

Source: Authors' calculation

Indian service providers are paid after meeting contractual obligations but need to spend money on inputs (salaries and wages, travel expenses, etc.) to achieve the same. This requires substantial provision for meeting predictable expenses (like salaries and wages) and unpredictable ones (like unforeseen crisis handling, travels, etc.) before payment is realised. But the ability of a firm to maintain CBB also depends on its financial ability (profitability) to do so, which in turn, also depends on the external economic environment. Given this, we note that efficient firms maintained larger amounts in CBB than inefficient firms except during 2012-15. A closer inspection of the results reveals that this is due to the fact that a few very large firms turned inefficient during this period, as mentioned earlier. Barring this exception, we can say, in general, that efficient firms hold a greater amount of CBB than inefficient firms. Besides we have also analysed[4] trends in the use of physical capital and surplus funds for investment in financial assets. Broad trends are as follows. While physical capital (Net fixed assets & Capital work-in-progress) has declined from about 20 percent of total assets in 2006 to 15 percent in 2019 for the average efficient firm, it declined from 20 percent to 12 percent over the same period for the average inefficient firm. Both types of firms reduced dependence on physical capital over time, but inefficient firms managed with lower physical capital than efficient firms. Discussions with industry professionals reveal the factors behind this decline. Indian IT firms have experienced a shift in their business models and service offerings from traditional IT infrastructure and hardware-focused services to digital services, software development, and cloud-based solutions, requiring less investment in physical assets such as buildings, machinery, and hardware. Instead, they focused on digital infrastructure, software licenses, and intellectual property, adopting an asset-light approach leveraging cloud computing, virtualisation, and remote infrastructure management. These firms optimise costs and improve operational efficiency by leveraging shared infrastructure and remote access. They increasingly rely on outsourcing and partnerships to provide specialised services or access specific technologies that reduce the need for large-scale investments in physical capital, as they can leverage the infrastructure and capabilities of their outsourcing partners or collaborate with other organisations to meet client requirements. These firms prioritise agility and flexibility in their operations, which may involve short-term leases, shared office spaces, or remote work arrangements. These practices reduce the need for extensive investments in long-term physical assets.

Next, coming to the impact of firm-specific factors like age, size, outward orientation (defined as a percentage of foreign revenue to total revenue), and firm specialisations on the inefficiency of inputs and outputs, we use random-effect panel regression[5]. Since the ADD-DEA model generates inefficiency (rather than efficiency) values, a negative (positive) sign of a coefficient indicates an influence towards

[4] See supplementary material for results.

[5] Choice of Random-Effect model is suggested due to the presence of a few time-invariant variables like firm specializations.

reducing (increasing) inefficiency. We checked for endogeneity using the Durbin–Wu–Hausman test (augmented regression test), suggested by Davidson, R. and J. G. MacKinnon (Davidson & MacKinnon, 1993). After checking for endogeneity for the explanatory variables with respect to the dependent variable (slacks in total revenue, EBITDA, COGSS, SGAE, and TL), we find the presence of endogeneity for the outward orientation only for total revenue, EBITDA, and COGSS slacks. To address this endogeneity, the endogenous variable is instrumented by its lagged value (Ullah et al. 2021). We use the generalised two-stage least squares (G2SLS) - random-effect IV estimator. For COGSS slack, we have used a one-period lagged value, and for revenue and EBITDA slacks, we have two-period lagged values of outward orientation that successfully tested the Hauman tests and Hansen-J tests. Given the structure of the industry, outward orientation can fluctuate from one financial year to another, depending on external conditions, like contracts being signed and delivery (leading to cost consumption) in one year, while revenue flows in the subsequent years. As such, the lag values of outward orientation should not have any association with the error terms in all these cases. We have used total revenue as a proxy for size. As a robustness check, we have also used NFA as an alternate proxy for size, but the results do not vary. The regression results are furnished in Table 6.

In line with the empirical literature on this sector in the Indian context, firm size is not at all significant for any of the input or output inefficiency. Firm age has no statistically significant influence on any of the input inefficiencies and revenue (output) inefficiency. However, older firms have lower EBITDA inefficiency than younger firms, possibly due to greater maturity in delivery capability achieved over time. It is to be noted that dependent variables like EBITDA are inefficiency scores of the sample firms. A negative coefficient of an explanatory variable implies that this variable tends to have a positive influence on the efficiency of firms.

Greater is the outward orientation, lower is the COGSS inefficiency, and higher is the inefficiency of SGAE, TL (inputs), and EBIDTA (output). The effect on COGSS inefficiency can be explained by the fact that greater outward orientation leads to a higher share of revenue earned in foreign exchange (mostly USD). However, COGSS is incurred mostly in domestic currency, which has almost continuously depreciated against USD during the sample period. The effect on SGAE inefficiency is due to the fact that a greater outward orientation also leads to more expenses arising out of greater marketing efforts, travel expenses, and so on. Greater outward orientation leading to higher TL inefficiency may be explained by uncertainty – greater outward orientation exposing firms to greater uncertainty, leading them to build an expanding buffer by retaining a bigger part of the profits over the years. The effect on EBIDTA inefficiency is partly the outcome of the inefficiency of the inputs (SGAE and TL) and partly due to the possibility that firms with greater outward orientation have, in general, lower managerial capability to monitor the profitability aspects of the business.

Table 6. Regression estimation results - G2SLS

Dependent variable		**COGSS Slack**	**SGAE Slack**	**TL Slack**	**Revenue Slack**	**EBIDTA Slack**
Age	Coefficient	0.0013	0.0024	-0.00073	0.0131	-0.0265**
Size (total revenue)	Coefficient	-1.11e-07	-3.86e-07**	-1.99e-07	-7.17e-07	-6.13e-07
Outward orientation	Coefficient	-0.0630**	0.1680*	0.0830*	-0.4059	0.9209**
Exchange Rate	Coefficient	-0.0023*	0.0094*	0.0039*	-0.0246**	0.0282**
Industry Specialization	Coefficient	-0.0180	0.0510	-0.0225	-0.3426	0.0154
Business Type	Coefficient	-0.0024	-0.0278	0.0476	-0.2642	-0.2199
Market Focus	Coefficient	-0.0366	-0.0475	-0.1076	1.2261*	-0.1715
Constant	Coefficient	0.2468*	-0.3513*	0.1391**	1.6914**	-0.7932
Fit statistics						
Wald χ^2		15.91**	134.4*	26.75*	14.96**	13.61 p-value 0.058
Instrumented		Outward orientation	NA	NA	Outward orientation	Outward orientation
		1-year lag			2-year lag	2-year lag
Hausman test		Prob > chi2 =0.0000	NA	NA	Prob > chi2 = 0.0390	Prob > chi2 = 0.0000
Hansen test		0.000 (equation exactly identified)	NA	NA	0.000 (equation exactly identified)	0.000 (equation exactly identified)

Notes: For COGSS slack, we have used a one-period lagged value and for Revenue and EBIDTA slacks, we have used a two-period lagged value of outward orientation due to the presence of endogeneity. Hansen J Statistic: H0: Over-identification restrictions are valid (p-values are in parentheses). Hausman Test: H0: specified endogenous variables can be treated as exogenous (p-values are in parentheses). The t-statistics are in parentheses, (*) $p < 0.01$, (**) $p < 0.05$, (***) $p < 0.1$. Going by the p-value of the $\chi 2$ statistic, models explaining inefficiency in COGSS, SGAE, TL, and total revenue are a good fit, but not when inefficiency on EBITDA is used as the dependent variable.

Exchange rate movements exert a positive influence on COGSS inefficiency on the input side and revenue inefficiency on the output side but a negative influence on the inefficiencies of the other inputs (SGAE and TL) and output (EBIDTA). Given that the movement of the exchange rate (INR/USD) has been in the direction of depreciation of INR during the period under study, the inefficiency of COGSS reduces primarily because wages are paid in INR and a significant portion of the revenues are earned in foreign exchange. Similar is the explanation for the effect of revenue inefficiency. More interesting is the effect of exchange rate movement (mostly depreciation in INR against USD) towards making the firms more inefficient in respect of SGAE and TL (inputs), and EBIDTA (output) – the common denominator being contractual obligation faced by the Indian service providers that bind them to one part of the cost of input (manpower) and one part of the output (revenue). It may be noted that the input TL (issued and outstanding equity and accumulated retained earnings) are mostly contracted in INR and serviced (by way of dividends, share buybacks, and the likes) in INR, and a part of SGAE is expended in foreign exchange. Finally, market focus (dummy variable) has the effect of increasing revenue inefficiency but has no statistically significant influence on the inefficiency of other output and input variables. That is, firms catering to the domestic economy alone are more inefficient than firms that cater to the global (along with or without domestic) markets in respect of revenue inefficiency. This is due to two factors. First, the average value of a contract from foreign clients is much higher than that from an Indian client. Second, efforts required to win low-value contracts from Indian clients are relatively larger in value terms. Indian IT & ITeS firms cannot ignore the clients from the Indian economy! Last but not least, firm-level choices like industry specialization (e.g., catering to only one sector, for example) and business type (e.g., offering IT consulting services only or other services as well) have no significant influence on inefficiencies of any of the inputs or outputs considered in this work. The number of efficient and inefficient firms is shown in Figure 6, while the number of efficient firms based on these classifications is given in Table 7.

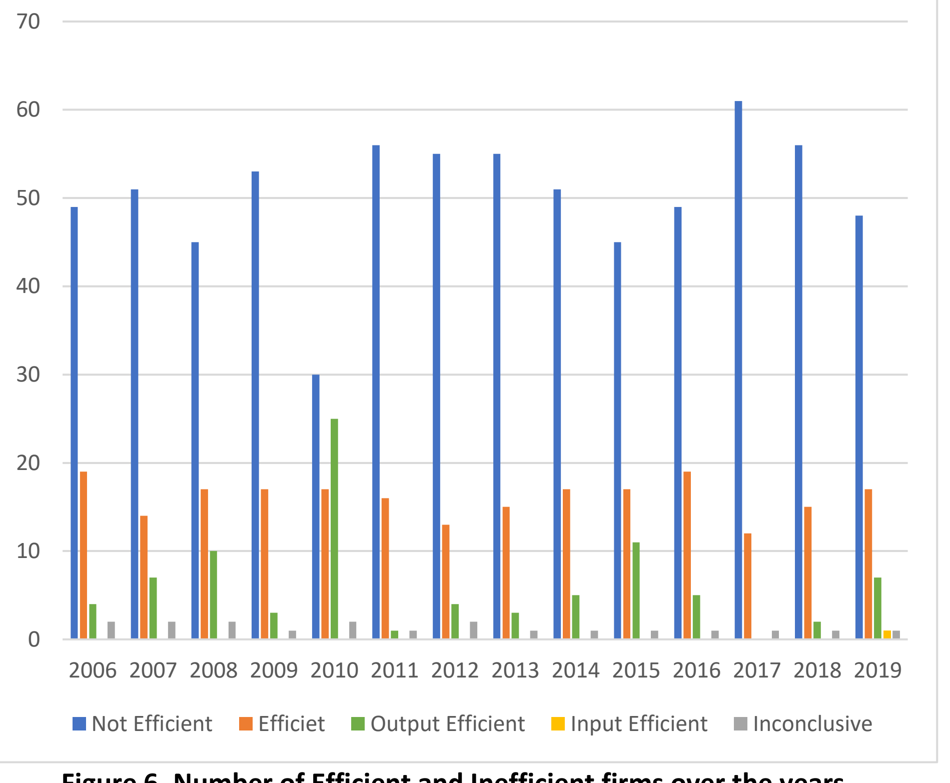

Figure 6. Number of Efficient and Inefficient firms over the years

Source: Authors' calculation

Table 7. Number of efficient firms based on various classifications

Year	Industry Specialization - All Sectors	Industry Specialization - Specialized	Business Specialization - IT Consultancy	Business Specialization - Others	Geo Specialization - Domestic and Global	Geo Specialization - Only Domestic
2006	10	9	9	10	17	2
2007	10	4	6	8	13	1
2008	11	6	8	9	13	4
2009	13	4	10	7	16	1
2010	12	5	7	10	14	3
2011	9	7	8	8	12	4
2012	9	4	6	7	9	4
2013	10	5	9	6	11	4
2014	12	5	7	10	14	3
2015	12	5	10	7	12	5
2016	13	6	10	9	15	4
2017	7	5	7	5	8	4
2018	12	3	9	6	13	2
2019	12	5	14	3	17	0

Source: Authors' calculation

5. Conclusion

This study has applied an integrated BSC-DEA method to evaluate the performance of Indian IT & and ITeS firms. The study finds a greater number of in-efficient firms than efficient firms. Furthermore, for inefficient firms, input inefficiency is more than output inefficiency. This may be because there is an output target but no specific input restrictions. These inefficient firms also have the scope for improvement for effectively utilising their assets. The results show that efficient firms have recorded higher and growing average revenue and average EBITDA and reported much higher and consistent average return on equity (ROE) than inefficient firms. The study further reveals the factors influencing the performance of these firms. While firm characteristics like its age, industry specialisation, and business type have no influence, factors like exports, exchange rate changes, and market focus impact its performance.

These results have critical policy implications for this sector. To reduce inefficiency, the inefficient firms should focus on controlling SGAE-related costs and reducing excess total liability (e.g. by increasing dividend pay-out and/or resorting to share repurchase). Another way for these inefficient firms to reduce future profits (and hence retained profits) could be to prospectively increase spending on R&DE to create intellectual property and develop proprietary products, thereby helping them sustain competitive advantage over the medium to long run.

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Appendix

Table A1: Summary table for Input-Output parameters

Measures	**COGSS Slack**	**SGAE Slack**	**TL Slack**	**Revenue Slack**	**EBIDTA Slack**
Mean	16502.01	1253.77	33012.22	27344.38	8711.92
Standard Error	2045.73	136.91	3577.97	3406.37	1145.59
Median	948.5	107.35	2828.6	1394.3	326.55
Mode	1.3	0	108.5	1.8	1.1
Standard Deviation	65845.94	4406.81	115163.85	109640.68	36873.2
Sample Variance	4335688455	19419994.35	13262711635	12021079511	1359633234
Kurtosis	52.11	89.78	32.97	54.13	60.59024232
Skewness	6.613	7.6	5.48	6.68	7.07
Range	786419.6	75303	1054797.7	1313079.7	491386.1
Minimum	0.4	0	2.3	0.3	-26946.1
Maximum	786420	75303	1054800	1313080	464440
Sum	17096082.8	1298906.29	34200664.7	28328778.4	9025553.1
Count	1036	1036	1036	1036	1036

Source: Authors' calculation

Table A2: Summary table for Dependent and Independent variables for efficient firms

Measures	COGSS Slack ratio	SGAE Slack ratio	TL Slack ratio	Revenue Slack ratio	EBIDTA Slack ratio	Age	Sales	Outward_orientation_1
Mean	0	0	0	0	0	21.46	62557.98	0.36
Standard Error	0	0	0	0	0	0.4	12406.61	0.02
Median	0	0	0	0	0	21	3325.20	0.26
Mode	0	0	0	0	0	20	0.50	0.00
Standard Deviation	0	0	0	0	0	5.93	186099.17	0.37
Sample Variance	0	0	0	0	0	35.22	34632901851	0.13
Kurtosis	N/A	N/A	N/A	N/A	N/A	0.25	22.29	-1.52
Skewness	N/A	N/A	N/A	N/A	N/A	0.3	4.54	0.37
Range	0	0	0	0	0	35	1313079.70	1.00
Minimum	0	0	0	0	0	8	0.30	0.00
Maximum	0	0	0	0	0	43	1313080.00	1.00
Sum	0	0	0	0	0	4828	14075546.50	81.92
Count	225	225	225	225	225	225	225.00	225.00

Source: Authors' calculation; **Note**: N/A denotes Not Applicable

Table A3: Summary table for Dependent and Independent variables for Input-efficient firms

Measures	COGSS Slack ratio	SGAE Slack ratio	TL Slack ratio	Revenue Slack ratio	EBIDTA Slack ratio	Age	Sales	Outward_orientation_1
Mean	0	0	0	0	0.617552	29	14621.6	0.789825
Standard Error	0	0	0	0	0	0	0	0
Median	0	0	0	0	0.617552	29	14621.6	0.789825
Mode	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Standard Deviation	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sample Variance	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Kurtosis	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Skewness	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Range	0	0	0	0	0	0	0	0
Minimum	0	0	0	0	0.617552	29	14621.6	0.789825
Maximum	0	0	0	0	0.617552	29	14621.6	0.789825
Sum	0	0	0	0	0.617552	29	14621.6	0.789825
Count	1	1	1	1	1	1	1	1

Source: Authors' calculation; **Note:** N/A denotes Not Applicable

Table A4: Summary table for Dependent and Independent variables for Output-efficient firms

Measures	COGSS Slack ratio	SGAE Slack ratio	TL Slack ratio	Revenue Slack ratio	EBIDTA Slack ratio	Age	Sales	Outward_orientation_1
Mean	0.09	0.3	0.39	0	0	21.78	14860.55	0.48
Standard Error	0.02	0.03	0.03	0	0	0.94	7130.041	0.04
Median	0	0.2	0.4	0	0	20	1995.5	0.58
Mode	0	0	0	0	0	21	#N/A	0
Standard Deviation	0.15	0.31	0.25	0	0	8.80	66504.59	0.33
Sample Variance	0.02	0.09	0.06	0	0	77.45	4.42E+09	0.11
Kurtosis	1.28	-1.30	-0.86	N/A	N/A	3.98	50.5	-1.42
Skewness	1.51	0.43	0.15	N/A	N/A	1.75	6.94	-0.31
Range	0.56	0.92	0.89	0	0	47	540331.3	0.96
Minimum	0	0	0	0	0	9	8.7	0
Maximum	0.56	0.92	0.89	0	0	56	540340	0.96
Sum	8.05	25.1	34.10	0	0	1895	1292868	41.76
Count	87	87	87	87	87	87	87	87

Source: Authors' calculation; Note: N/A denotes Not Applicable

Table A5: Summary table for Dependent and Independent variables for Inefficient firms

Measures	COGSS Slack ratio	SGAE Slack ratio	TL Slack ratio	Revenue Slack ratio	EBIDTA Slack ratio	Age	Sales	Outward_orientation_1
Mean	0.15	0.37	0.49	0.56	0.76	23.1	18388.71	0.45
Standard Error	0.01	0.01	0.01	0.12	0.18	0.37	2821.63	0.01
Median	0.03	0.34	0.52	0.08	0.17	22	1023.9	0.48
Mode	0	0	0	0	0	23	8.8	0
Standard Deviation	0.19	0.33	0.29	3.16	4.76	9.72	74866.37	0.37
Sample Variance	0.04	0.11	0.08	9.98	22.69	94.5	5.6E+09	0.14
Kurtosis	1.49	-1.265	-1.04	411.43	169.47	7.82	37.24	-1.58
Skewness	1.39	0.33	-0.19	19.15	9.7	2.24	5.85	0.03
Range	0.97	1	0.99	72.77	113.24	69	731699.6	1
Minimum	0	0	0	0	-25.60	5	0.4	0
Maximum	0.97	1	0.99	72.77	87.64	74	731700	1
Sum	102.78	259.48	345.46	392.49	536.94	16262	12945650	317.55
Count	704	704	704	704	704	704	704	704

Source: Authors' calculation