Efficiency Assessment of Indian Textile Units Using Data Envelopment and Regression Analysis

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Abstract

Firms are always in the pursuit of improvizing their performance. Optimum utilization of resources and the eradication of sources of inadequacies result in improved performance and production for manufacturing firms. Improved performance and production lead to increased efficiency for the firms. In this study, data envelopment analysis was used to evaluate the efficiency using financial data of 11 years of all the 13 S&P BSE 500 listed textile firms. Consistent with the relevant literature, three inputs (power, fuel, & water charges ; compensation to employees ; and raw materials, stores, & spares) and one output (profit before tax) were selected. Additionally, outcomes from the DEA analysis were used to perform the regression analysis. Out of the 13 units analyzed for efficiency, two textile units were found to be operating efficiently. The results of the regression analysis showed that an increase in employee compensation will lead to an increase in profit since the increase in the compensation helps to increase motivation from job satisfaction. Besides adding value to the efficiency assessment literature, the research findings of this study also provide meaningful business insights for the practitioners for improving productivity performance by finding the core action area in resource planning decisions.

Keywords : productivity-performance, efficiency, benchmarking, data-envelopment-analysis, regression analysis

JEL Classification : C61, C67, D24, L25, L6

Paper Submission Date : April 8, 2020 ; Paper sent back for Revision : March 25, 2021 ; Paper Acceptance Date : April 20, 2021 ; Paper Published Online : July 5, 2021

Production and performance are equally important and hold immense significance for the manufacturing firms (Kang et al., 2018). Production competence is considered to be extremely domineering and vital by the manufacturing firms for improving their performance. To achieve the goal of overall performance enhancement by the manufacturing firms, firms need to ensure that the business strategies and production strategies should be aligned with each other, and manufacturing practices should continuously sustain the performance (Al-Surmi et al., 2020).

There are several ways to gauge the performance of the firms. One of the ways of assessing the performance is by adjudging the competitiveness of a firm (Bockholt et al., 2020). Firms always strive to maintain and improvise

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DOI : https://doi.org/10.17010/ijf/2021/v15i5-7/164490

their position compared to their competitors (Gupta & Khan, 2017). Another way of analyzing performance is through financial well being (Abdel-Basset et al., 2020).

Finally, the efficiency of the firms also demonstrates their performance. Efficiency relates to the capability of minimizing wastage of raw materials, time, energy, efforts, etc. (Nguyen et al., 2019). A firm is termed to be efficient when it is capable of optimally utilizing the resources at its disposal (Ramanathan, 2003). Interestingly, the increased efficiency of the firms enhances both competitive advantage and financial performance. Moreover, efficient firms can create value, and firms always thrive to become efficient by increasing their performance (Ramanathan, 2003).

Achieving the productivity performance target is challenging for manufacturing firms owing to various intrinsic and extraneous factors (Gambhir & Sharma, 2015a). The manufacturing firms face issues such as parity in production level ; economic policy changes ; fluctuations in global fuel prices ; managing wastages ; catering to governance, regulations, and geopolitical expectations ; following CSR norms ; adhering to sustainability practices, etc. (Piyathanavong et al., 2019). The manufacturing units need to brace for the unforeseen and unscheduled circumstances caused due to uncertainty and disruptions. Due to these challenges, it becomes difficult for the manufacturing units to make financial gains, acquire competitive advantage, and improve efficiency (Agostini & Filippini, 2019).

With the above backdrop, this paper attempts to measure the performance efficiency of the Indian textile manufacturing units over the period from 2006 – 2016. Data envelopment analysis (DEA) along with regression analysis is employed for this purpose. The performance efficiency of the textile units listed on the S&P BSE 500 is evaluated. The results of this study can help managers to improve their performance based on established performance indicators.

Review of Literature

Industry Context

The textile industry is one of the oldest and largest manufacturing industries of the world, and interestingly, India is among the top five global players (Hasanuzzaman, & Bhar, 2017 ; Raut et al., 2019). India is the third-largest producer of fibre with approximately 1,400 operating textile mills. India contributes 13% to the total exports in the world ; it has 7% output in value from the textile industry. Also, the textile industry contributes about 4% of India's GDP. Given the fact that the textile industry is a labour-intensive industry, it employs nearly 45 million workers (Indian Brand Equity Foundation, 2018 ; Ministry of Textiles, Government of India, 2018). As per a study conducted by FICCI (2016), the current global apparel market constitutes around 2% of the world's GDP and is worth US$ 1.7 trillion, which reflects the magnificence of the textile industry worldwide. The demand for apparels is expected to increase approximately by 4% and the projected compound annual growth rate for India is nearly 12%. Spending on the purchase of apparels is also expected to increase, thus creating substantial demand for apparels. To fulfil the anticipated surge in demand, the textile industry needs to adopt suitable policies.

With the formulation of the right kind of policies, the Indian textile industry has the potential to improvise its performance (Sharma & Narula, 2020). The termination of the agreement on textiles and clothing by the World Trade Organization (WTO, n.d.) made the Indian textile industry open and unrestricted from 2005 onwards because of the removal of limitations on global exports and imports by any country. This policy change has led to a substantial increase in the total textile-related exports by India. Though exports from the textile industry have increased phenomenally over the years, the quantity and value of exports still lag behind other Asian countries like China and Japan, which export up to seven times more than India (Gambhir & Sharma, 2015b).

Data Envelopment Analysis

Data envelopment analysis (DEA) was developed by Charnes, Cooper, and Rhodes in the year 1978 (Banker et al., 2019). DEA is a simplistic non-parametric test based on linear programming (Banerjee, 2018) used for evaluating the performance efficiency of homogenous entities or decision-making units (DMUs) (Dobos & Vörösmarty, 2019). The relative efficiencies of the DMUs are estimated using values of the analogous inputs and outputs utilized by the DMUs for measuring the optimum utilization of inputs to produce the given outputs by the firms. DEA helps in the identification of the sources of inefficiencies such as excessive utilization of resources or less than expected output accomplishment (Rashidi & Cullinane, 2019).

DEA is used to identify inefficient units and benchmarking. It provides the efficiency score of each DMU, slacks for the input and output used, and assigns ranks to the DMUs (Dobos & Vörösmarty, 2019). DEA is considered to be a better estimate of efficiencies because of many reasons. First, this method is a boundary method and it does not include mathematical hypothecations. Second, DEA provides flexibility in the selection of inputs and outputs. The third advantage is that it can be used to deal with multiple inputs and outputs without any requirement of making assumptions for the production relationship under consideration (Banker et al., 2019 ; Tran et al., 2019).

Further, DEA has evolved from the conventional CCR DEA developed by Charnes, Cooper, and Rhodes in the year 1978 to the contemporary BCC model (Aggelopoulos & Georgopoulos, 2017). In CCR DEA, a set of inputs and outputs is used to evaluate the relative efficiency of the DMUs at one point in time and this model caters to constant return to scale. The evaluation based on stationary time emerged as a drawback of this model (Izadikhah & Farzipoor Saen, 2015). Subsequently, the CCR DEA model was revised to facilitate the variable return to scale exhibiting different returns (increasing, constant, or diminishing to scale) at various points in the production frontier and this version of DEA is known as the BCC model (Barasa et al., 2019).

Interestingly, the decision for selection of the criteria for the mix of these inputs and outputs varies according to the types of firms and the industries. Inputs are selected considering resourcefulness, value addition to the firm, and the effect of environmental factors. Similarly, the outputs are an outcome in the form of goods, services, or other monetary benefits (Tran et al., 2019). Moreover, depending on the contextual relevance, DEA can follow the input orientation or output orientation approach. In the input orientation approach, an attempt is made to bring the consumption or the input utilization to the minimum level without affecting the outputs. Conversely, in an output orientation approach, the objective is to achieve the extreme level of output production, without increasing the existing resources (Biener et al., 2016 ; Gambhir & Sharma, 2015b). The input minimization perspective comes in handy when the management is looking for cost-cutting or downsizing, and the output orientation approach is preferred when the management makes strategies for market expansion (Bellandi & Santini, 2019).

DEA is used for efficiency assessment of the firms. A firm with the highest output to input ratio is termed as an efficient firm (Liu et al., 2019). The efficiency assessment includes evaluating human management, assessing the effectiveness of policies, reshuffling resources, identifying sources of inefficiencies, and ranking the firms across several industries. DEA has been used to assess the performance of the DMUs operating in various sectors and businesses such as manufacturing (Kang et al., 2018) ; schools and universities (Mikušová, 2015) ; towns and villages (Ibrahim & Salau, 2016) ; hospitals (Patel & Ranjith, 2018) ; banks (Khurana & Khosla, 2019) ; garment industry ; supplier selection (Kuo & Lin, 2012) ; courts, airlines, oil, and energy (Vikas & Bansal, 2019), etc.

Research Context

In the dynamic business world, which is under the great influence of globalization, every firm must minimize the expenditure of its capital to ensure cost-effective manufacturing and profitable business (Kang et al., 2018).

As is highlighted by researchers that factors such as shortening product life cycles, increasing consumer expectations, and diminishing physical distance hamper the profitability of the firms (Bosman et al., 2019), hence any research work should focus on resolving the concerns raised by researchers.

Firms can appraise their performance through financial well being, competitive advantage, and efficiency (Barasa et al., 2019). This research is premised on the efficiency assessment studies on manufacturing firms of developed countries because there is a dearth of such work with regards to emerging markets (Mathiyazhagan et al., 2019). Research work on efficiency assessment facilitates improvement in the performance of the manufacturing firms (Agostini & Filippini, 2019 ; Bhullar & Singh, 2017).

In the extensive literature review, it is found that the efficiency and performance analysis of the textile industry has not been carried out recently. More specifically, negligible work has been conducted about contemporary issues of the textile industry. Gambhir and Sharma (2015a) conducted an assessment of the efficiency of the Indian textile industry, which was used as a base for evaluating the efficiency and performance of the Indian textile industry by focusing on the contemporary challenges. Substantial research should be performed to improve and enhance the insights of the existing research works (Gupta & Kumar, 2018).

Objectives of the Study

From the perspective of research and practice, it becomes vital and imperative to assess the efficiency of the textile industry. By comprehensively analyzing the efficiencies of the textile units, this study aims at making a remarkable threefold contribution to the literature by : (a) analytically establishing the optimum resource allocation strategies and thus providing the basis for further research, (b) amalgamating two techniques, DEA and regression, for evaluating the efficiency of the firms operating in the Indian textile industry, (c) providing empirical evidence for optimization of resources to enable strategic decision making and maximize profit.

This research work has two specific objectives, which are :

- To find the most efficient textile unit,
- To determine the most significant resource for an efficient unit.

Research Methodology

In this research study, DEA has been used to assess the efficiency of the manufacturing units operating in the Indian textile industry. Further, regression analysis is also performed on the data of the firms which emerged efficiently in the DEA analysis. This is done with the intention to study the relationship between the inputs and the outputs used by the firms and with the perspective of finding the impact of a percent change in inputs used by the efficient firms relative to the change in the output (Davtalab - Olyaie, 2019).

Sample

This study attempts to perform an efficiency-based comparative study of the Indian textile units listed in S&P BSE 500 to assess the performance of these manufacturing firms. The S&P BSE 500 index consists of the top 500 Indian liquid stock companies representing more than 90% of the total market capitalization of the exchange (Kar & Jena, 2019). DEA is used to provide sharper insights into the efficiency of all 13 BSE 500 listed textile decision-making units (DMUs). These units are homogenous and comparable. Similar inputs-used and outputs-produced are considered to measure the efficiencies of these DMUs.

The period for the study was chosen very judiciously. The beginning year is taken as 2005 – 06 to apprehend the impact of highly industry-specific WTO policy changes in the year 2005. Similarly, the ending period is 2015–16, which embarked several global and country-specific economic events. For example, the Chinese stock market crashed badly in 2016 and India overtook China as the fastest-growing economy. In the Indian context as well, crucial events occurred such as demonetisation (November 2016) and implementation of the Goods and Services Tax (July 2017). The occurrence of these events had a major impact on the Indian economy which led us to choose the ending financial year as 2015–2016. Hence, data for the period ranging from financial years 2005–06 to 2015–16 were utilized to capture the impact of change in WTO policy.

Data Collection

For this research work, secondary data from the Prowess database was used. Prowess is a database of Indian firms compiled by the Centre for Monitoring Indian Economy. This database includes published financial statements of the firms without regrouping the data in any form, and the data is highly reliable because it is not distorted. The longitudinal data were used to calculate the efficiency and evaluate the consistency of performance over a period. The average value for the data of the entire period of 11 years for each input and output was calculated. These mean values were used to perform DEA to find the efficient DMUs and subsequently, regression analysis was performed on the efficient DMUs to understand the impact of the inputs utilized on the output produced.

Input and Output Variables

The choice of input and output variables is very critical for performing DEA. The chosen variables should reflect the goals and objectives of the DMUs under consideration. In this study, the variables or performance indicators were chosen based on the literature of similar context (Gambhir & Sharma, 2015b). These are the factors proposed in the literature to be having an excessive influence on the productivity and performance of the textile manufacturing units.

The inputs and outputs for the study were selected based on two criteria : (a) importance and suitability with regards to the textile industry and (b) maintaining consistency with the variables proposed in the existing literature. We have used power fuel and water charges, compensation to employees and raw materials, stores and spares as the inputs and profit before tax as the output as was used by Gambhir and Sharma (2015a, 2015b). A multiple inputs and single output model has been used for the analysis. Parameters and their acronyms are mentioned below :

Profit before Tax	:	PBT
Power, fuel & water charges	:	PFW
Compensation to employees	:	CtE
Raw materials, stores & spares	:	RSS

Also, while performing DEA, along with the selection of the inputs and the outputs variables, a rule of thumb for the selection of the number of DMUs has to be followed. This rule states that the number of DMUs for the analysis should be at least three times more than the number of inputs and outputs. So, if 'n' number of inputs and 'm' number of outputs are used for the analysis, then :

$$\text{Total Number of DMUs} >= \text{Max}\ \{n \times m,\ 3(n+m)\} \qquad \text{.......... (1)}$$

DEA and Regression

DEA caters to the assumption of economies of scale and comprises of two models namely the CCR and BCC models which embrace the concept of input minimization and output maximization. In the present research work, both the output maximization CCR model (Davtalab - Olyaie, 2019) and the input minimization BCC model (Halkos & Petrou, 2019) have been used to find the efficiency scores of the considered DMUs.

The present research work uses a combination of cross-sectional and time-series data. The financial data of 11 years for the considered DMUs is utilized for performing DEA. For an in-depth understanding of the dependence relationship, panel regression analysis has been conducted between the dependent variable PBT and independent variables PFW, CtE, and RSS of the efficient DMUs. This is done to perform a comprehensive analysis and to ensure the robustness of the results.

DEA and regression analysis are the two techniques that have been used together for performing the analysis in this research work. Generally, only DEA is used for finding the efficiency of the decision-making units. In this study, the efficiency assessment is performed in two steps and is supported by another analysis for sharper insights into the resource management decisions. In the first step, DEA is used to decipher the resource utilization (output to input ratio) by the manufacturing firms to find the efficient units. Subsequently, regression analysis is used to determine the most significant input for the given output in the case of the efficient units. The amalgamation of two techniques helps in comprehensively evaluating the efficiency concerns of the textile units, and thus, increases the robustness of the results presented in the study.

Analysis and Results

Descriptive Statistics

The descriptive statistics of the DMUs considered for this research work are shown in Table 1. It includes the

Table 1. ***Descriptive Statistics (in ₹ Million)***

S. No.	Company	*PBT*		*PFW*		*CtE*		*RSS*	
		Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
1	Arvind Ltd.	2359.76	1932.79	3027.31	1107.65	3575.4	1660.93	15640.57	7126.80
2	Bombay Dyeing	–980.76	1173.92	970.16	264.84	713.99	215.31	9675.48	3444.6
3	Himatsingka Seide Ltd.	394.71	639.65	421.2	187.17	612.13	282.86	3291.69	1807.43
4	Indo Count Inds. Ltd.	560.68	1185.88	402.89	161.99	396.62	258.23	5636.43	3790.65
5	J B F Industries Ltd.	1169.21	597.39	1664.65	824.28	418.28	233.66	24820.73	9947.55
6	K P R Mill Ltd.	1089.46	617.63	523.08	421.86	680.37	430.49	7467.37	3806.02
7	Kitex Garments Ltd.	542.97	528.53	101.23	62.12	454.74	183.29	1500.69	573.71
8	Page Industries Ltd.	1304.36	1087.95	48.182	34.66	1157.61	960.41	2827.09	2083.12
9	Raymond Ltd.	376.92	1442.54	1072.54	236.78	2931	718.62	5681.15	1390.22
10	Swan Energy Ltd.	248.37	220.60	20.68	20.065	34.12	35.26	1821.54	1277.48
11	Trident Ltd.	910.06	1084.32	1935.35	974.13	2105.32	1122.56	12723.34	6520.79
12	Vardhman Textile Ltd.	4176.02	2572.93	4077.35	1223.63	2287.26	921.45	19433.64	7403.94
13	Welspun India Ltd.	2154.06	2868.94	2030.56	1001.45	1703.24	977.75	12899.72	6909.74

Table 2. *Descriptive Statistics of the Variables (in ₹ Million)*

Variables =>	*PBT*	*PFW*	*CtE*	*RSS*
Max	9008.9	6590.3	6078.3	38074.7
Min	–3163	0.41	0.3	193.3
Average	725.07	926.11	1189.05	7826.01
SD	1255.62	1249.05	1108.77	7607.01

average and standard deviation of the 11 - year financial data (in ₹ million) related to the inputs and outputs of the chosen DMUs.

Table 2 contains the descriptive statistics of the inputs and the outputs across the industry for the entire period. It includes the maximum, minimum, average, and standard deviation values of the variables individually.

DEA Efficiency Scores

Efficiency scores for the considered DMUs are calculated using the average scores of the 11 years data of the inputs and the outputs used by these DMUs. The calculations were undertaken using DEA software. The calculated efficiency scores are used to assign ranks to the DMUs using the input minimization BCC model (Table 3) and output maximization CCR model (Table 4). Both Table 3 and Table 4 include the first column named '*DMU* ' which refers to the various DMUs under consideration. The second column is named '*Eff* ' and it lists the technical efficiency score of each DMU. The third column is named '*Rank* ' and it refers to the new rank assigned to the DMUs as per the results obtained after performing the analysis. The fourth column is the '*Peers*' column and it includes the DMU number that should be benchmarked by the DMU of that particular row. For instance, as per the results demonstrated in Table 3, DMU 9 should benchmark DMU 7. The peers' column is followed by the fifth column of '*Weights*' which provides the details in the form of weights regarding the importance that should be

Table 3. *Input Minimization BCC Model Results*

DMU	Efficiency	Rank	Peers	Weights	Count
1	0.57	9	8, 12	0.63, 0.37	None
2	0.18	13	7, 10	0.23, 0.77	None
3	0.49	10	7, 10	0.63, 0.37	None
4	0.64	8	6, 8, 10, 12	0.06, 0.01, 0.75, 0.03	None
5	1.00	4			None
6	1.00	5			2
7	1.00	3			3
8	1.00	2			4
9	0.26	12	7	1.01	None
10	1.00	1			5
11	0.28	11	8, 10, 12	0.33, 0.59, 0.08	None
12	1.00	6			4
13	0.78	7	6, 8, 10, 12	0.35, 0.27, 0.05, 0.34	None

Table 4. *Output Maximization CCR Model Results*

DMU	Efficiency	Rank	Peers	Weights	Count
1	0.49	8	8, 10	2.97, 3.97	None
2	0	13	None	NA	None
3	0.44	9	8, 10	0.50, 1.03	None
4	0.55	7	8, 10	0.26, 2.69	None
5	0.38	10	10	12.26	None
6	0.74	5	8, 10	0.49, 3.34	None
7	0.97	4	8, 10	0.39, 0.22	None
8	1.00	2	NA	NA	9
9	0.14	12	8	2.01	None
10	1.00	1	NA	NA	9
11	0.28	11	8, 10	1.69, 4.36	None
12	0.98	3	8, 10	1.74, 7.97	None
13	0.72	6	8, 10	1.32, 5.03	None

given to the DMUs which are benchmarked (Kuo & Lin, 2012). The last and sixth column of '*Count*' provides the count of the number of DMUs that are referring to the DMU of that particular row for benchmarking.

As shown in Table 3, DMUs 5, 6, 7, 8, 10, and 12 emerge as the most efficient units through the input orientation analysis. These are the six DMUs that are operating efficiently. The possible reason for more than one DMU to be efficient is merely because one DMU might be better in optimum utilization of one resource as compared to the other efficient DMUs, which might demonstrate better management in some other criteria. Hence, more than one DMU can become efficient owing to one or the other form of optimum resource utilization. Further, DMU 10 is referred for benchmarking by the maximum number of DMUs ; hence, it is considered to be the best DMU. DMU 2 has the least efficiency score of 0.18, demonstrating that this DMU is the most inefficient unit as far as resource utilization is concerned. Also, this DMU needs to benchmark DMUs 7 and 10 with a weight of 0.23 and 0.77, respectively.

Table 4 contains the results for the output maximization CCR model and shows that DMU 8 and 9 have an efficiency score of one. Thus, they are considered to be the most efficient units in terms of output production. Here, there is a tie between DMU 8 and 10 concerning the efficiency scores ; in such situations, the tiebreaker is the number of units referring to these DMUs for benchmarking. In this case, number of DMUs referring to DMU 8 and 9 is equal, which is again a tie. Hence, it can be said that both units are performing equally well. The least efficiency score is 0.14 for DMU 9, which means that DMU 9 is the DMU that needs to work on increasing its output production with the available resources. Also, it is suggested through the analysis performed in this research work that the DMU 9 should benchmark DMU 8 for increasing its efficiency. Moreover, it can be observed from the results shown in Table 3 and Table 4 that DMUs 8 and 10 are efficient in both models. This means that these DMUs are efficient in both input minimization as well as output maximization. This further demonstrates that the decision-makers of these DMUs are capable of optimally utilizing the resources available at their disposal and also these DMUs can proficiently maximize their profits.

Scale Efficiency

The efficiency scores from the input minimization BCC model and output maximization CCR model are used to

Table 5. ***Efficiency Scores***

S.No.	CCR Score	BCC Score	SE Score
1	0.49	0.57	0.86
2	0	0.18	0
3	0.44	0.49	0.90
4	0.55	0.64	0.86
5	0.38	1.00	0.38
6	0.74	1.00	0.74
7	0.97	1.00	0.97
8	1.00	1.00	1.00
9	0.14	0.26	0.54
10	1.00	1.00	1.00
11	0.28	0.28	1.00
12	0.98	1.00	0.98
13	0.72	0.78	0.92

Table 6. ***Statistics of Efficiency Scores***

Scores	No. of Efficient DMUs	Percentage	Min	Max	Avg.	*SD*
BCC	6	46	0.18	1	0.71	0.32
CCR	2	15	0	1	0.59	0.34
SE	3	23	0	1	0.78	0.30

Table 7. ***Value in Percentage for BCC Scores***

	PBT	*PFW*	*CtE*	*RSS*
Efficient	59.63	39.49	29.48	48.87
Inefficient	40.37	60.51	70.52	51.13

Table 8. ***Value in Percentage for CCR Scores***

	PBT	*PFW*	*CtE*	*RSS*
Efficient	10.85	0.42	6.98	3.93
Inefficient	89.15	99.58	93.02	96.07

calculate the scale efficiency scores for the DMUs as shown in Table 5. Scale efficiency is the ratio score and is calculated by dividing the CCR scores with the BCC scores (Vikas & Bansal, 2019). In the present research work, three DMUs emerge to be efficient as per the scale efficiency scores, and these DMUs are DMU 8, 10, and 11.

Table 6 includes the summary statistics for all three types of scores. Six DMUs emerge as efficient in the input minimization BCC model, two DMUs in the output maximization CCR model, and finally, three efficient DMUs are found through the scale efficiency scores. It also includes the percentage of the efficient DMUs ; 23% of the DMUs are efficient as per the scale efficiency scores.

Table 7 and Table 8 show the role of the efficient and inefficient firms on the input and output variables for the

Table 9. ***Returns to Scale***

S. No.	SE Score	RTS
1	0.86	Variable
2	0	Variable
3	0.90	Variable
4	0.86	Variable
5	0.38	Variable
6	0.74	Variable
7	0.97	Variable
8	1.00	Constant
9	0.54	Variable
10	1.00	Constant
11	1.00	Constant
12	0.98	Variable
13	0.92	Variable

Table 10. ***Present and Future Targets for Inefficient Firms***

DMU Name	*PFW*	*CtE*	*RSS*	Present Value for PBT	Target Value for PBT
Arvind Ltd.	3027.31	3575.40	15640.57	2359.75	4863.05
Bombay Dyeing	970.16	713.99	9675.48	–980.76	NA*
Himatsingka Seide Ltd.	421.20	612.13	3291.69	394.71	906.73
Indo Count Inds. Ltd.	402.89	396.62	5636.43	560.68	1010.63
J B F Industries Ltd.	1664.65	418.28	24820.73	1169.21	3044.62
K P R Mill Ltd.	523.08	680.37	7467.37	1089.46	1467.80
Kitex Garments Ltd.	101.23	454.74	1500.69	542.97	559.50
Raymond Ltd.	1072.54	2931.00	5681.15	376.92	2621.17
Trident Ltd.	1935.35	2105.32	12723.34	910.06	3287.87
Vardhman Textiles Ltd.	4077.35	2287.26	19433.64	4176.02	4249.63
Welspun India Ltd.	2030.54	1703.24	12899.72	2154.05	2974.71

Note. *Since the average PBT for Bombay Dyeing is negative, there is no target value suggestion for it.

BCC and CCR models, respectively. Table 9 contains the details about the returns to scale at which the firms are currently operating.

Table 10 includes the present as well as future target output for the inefficient firms. If the inefficient firms can achieve future target outputs as shown in the table, then these firms can also become efficient.

Correlation Analysis

The correlation matrix is calculated for the variables using the financial data of the 11 years under consideration and is shown in Table 11. The value of the correlation provides a suggestion about the relationship between the variables taken into account for the industry as a whole.

Table 11. *Correlation Matrix*

Correlation	*PBT*	*PFW*	*CtE*	*RSS*
PBT	1			
PFW	0.792	1		
CtE	0.882	0.964	1	
RSS	0.734	0.981	0.924	1

From the correlation matrix, it can be noted that all variables show a high degree of relationships among themselves. The highest value of correlation is 0.98 ; this highest correlation is between RSS and PFW. When we consider the correlation between the inputs and the output, PBT is found to be highly correlated with CtE at a value of 0.88. As these two variables are highly correlated, it can be interpreted that the change in CtE will positively influence the change in PBT.

Regression Analysis

Manufacturing units looking for market expansion prefer output maximization, which means that units are willing to increase their output while maintaining their present level of inputs. The reason for the preference of the output orientation perspective by the manufacturing units is that the decision-makers and stakeholders always want to maximize their outputs while maintaining a minimum or least level of inputs. To understand the impact of the optimum utilization of the considered inputs on the output produced by the DMUs, the three efficient units (DMUs 8, 10, and 11) are considered for performing the regression analysis (Table 12). The reason for not considering the inefficient units for the regression analysis is that they might influence the results by overestimating or underestimating the relation of the inputs and the outputs.

With the obtained intercept value, it can be predicted that when the value of all the three independent variables is zero, the value for PBT is 106.21 million. Hence, it can be argued that all three DMUs are making a profit (before tax) without incurring any of the cost under consideration. The PFW and CtE are significantly affecting the output, which is PBT at a 5% level of significance. PFW is negatively related to PBT, as estimated by the value of coefficient b_1. The value of b_1 estimates that when the cost of PFW decreases by 1 rupee, the profit before tax increases by 0.64 rupees. So, these companies can increase the PBT by optimizing the utilization of their PFW costs. In the same line, RSS is also negatively related to PBT as estimated by the value of coefficient b_3, which indicates that when the company reduces the cost of RSS, the PBT will increase by 0.02 rupees. However, the relation is not significant. On the other side, CtE is positively related to PBT as estimated by b_2. The value of b_2 shows that when CtE increases by 1 rupee, the PBT will also increase by 1.12 rupees.

Table 12. *Relationship Between Profit Before Tax and the Costs*

Independent Variable	Coefficients	Std. Error Coefficient	*P*-value
Constant	106.21	149.38	0.48
(PFW) × 1	–0.64	0.32	0.05
(CtE) × 2	1.12	0.14	0.00
(RSS) × 3	–0.02	0.06	0.80

Note. *F* - value = 0.0000   *R* - square = 0.75   Adjusted *R* - square = 0.73.

Conclusion

In this research work, a comparative analysis of the leading textile units is performed by establishing their efficiencies using DEA. The objective of conducting this research work is to assess and compare the performance of homogenous DMUs. Hence, the dynamic and relative efficiency of all BSE 500 listed textile companies of India are studied. Two units namely Page Industries Limited and Swan Energy Limited are found to be efficient with respect to their resource utilization as well as profit maximization. Interestingly, both these companies are not the market leaders, but the results of this research work reflect that these firms are performing efficiently compared to their analogous peers.

Some well-known firms such as Arvind Ltd., Bombay Dyeing, and Wellspun have a wider market share and better market reputation but have a possibility for increasing the efficiency and maximizing profit by optimizing their resource utilization. All the inefficient firms can become efficient by optimum utilization of their resources. Cost-cutting could be one such mechanism of ensuring optimum or least utilization of the resources. Profit maximization can be achieved by benchmarking the efficient units.

Regression analysis is also used to estimate the relation of the resources utilized to the output produced by the efficient units. The inputs PFW and CtE are found to be significantly affecting the output PBT. Input variable CtE is found to be positively related to PBT, which shows that an increase in the employee compensation will lead to an increase in the profit-making ; this may be attributed to the fact that an increase in the compensation will lead to increased motivation from job satisfaction. RSS is negatively related to the PBT, this shows that the firms need to optimize the use of raw materials and other inventories. The input variable PFW also has a negative relation with PBT ; so, it can be inferred that the inefficient DMUs need to focus more on reducing the consumption of PFW.

Implications

Managerial Implications

The input resources are the most critical elements for the firms operating in the manufacturing industry as the industry uses a large quantity of raw materials and energy resources. Most of the resources consumed are non-renewable sources of energy and thus need more sensitivity in their utilization. For instance, in the manufacturing of the processed polyester-fabric by the textile firms ; currently, the cost of energy, water, coal, and electricity is about 40% of the total cost ("Textile mills tie up with GEDA," 2018). The insights of this study shall be useful for the decision-makers of the manufacturing textile firms. Best practices such as optimum utilization of resources will not only leverage the textile firms in increasing their profits, but will also contribute to the society at large by helping the firms in performing their social responsibilities (CSR), thus gaining the confidence of their stakeholders including customers (Piyathanavong et al., 2019).

Policy Implications

A major concern for any firm in high energy price fluctuations is to improve their energy efficiency. Initiatives should be taken for increasing knowledge about energy efficiency technologies. For example, training campaigns may be organized for the manufacturing firms (Nguyen et al., 2019). The results of the study shall help the policymakers in formulating effective governance mechanisms directed towards the textile firms, especially in emerging markets. The government is also keen on taking initiatives by offering inputs to minimize the consumption of various natural resources. For example, Gujarat Energy Development Agency and Man-made

Textile Research Association have collaborated to ensure a reduction of energy utilization by the textile firms of Gujarat. Optimum utilization of the resources leads to profit realization and enables the firms to give back to society by taking care of the environment (Dobos & Vörösmarty, 2019 ; Mathiyazhagan et al., 2019).

Limitations of the Study and Scope for Future Research

The efficiency of companies is a complex issue in nature. Any method used for efficiency evaluation has its advantages and limitations ; hence, an integrated approach is advisable. The limitation of this study is that only one way of benchmarking a company's performance has been proposed. The selection of the outputs and the inputs might be examined further ; though the inputs and outputs considered in this work are appropriate, but at the same time, they are contextual. Another limitation of this study is its geography specificness; so, a scope of future study could be a cross-country analysis.

Authors' Contribution

Dr. Chetan A. Jhaveri conceived the idea of this research work and developed the underpinning qualitative and quantitative designs to undertake the research study. He also supervised the study from conception to finalization. Gunjan Sood extracted research papers with high repute, filtered these based on keywords, and wrote the manuscript in consultation with both the authors. Riya Shah and Dr. Jhaveri executed the analytical methods and did the numerical computations for the research work using OSDEA and EViews software.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter, or materials discussed in this manuscript.

Funding Acknowledgement

The authors received no financial support for the research, authorship, and/or for the publication of this article.

References

Abdel-Basset, M., Ding, W., Mohamed, R., & Metawa, N. (2020). An integrated plithogenic MCDM approach for financial performance evaluation of manufacturing industries. *Risk Management, 22*(3), 192 – 218. https://doi.org/10.1057/s41283-020-00061-4

Aggelopoulos, E., & Georgopoulos, A. (2017). Bank branch efficiency under environmental change : A bootstrap DEA on monthly profit and loss accounting statements of Greek retail branches. *European Journal of Operational Research, 261*(3), 1170 – 1188. https://doi.org/10.1016/j.ejor.2017.03.009

Agostini, L., & Filippini, R. (2019). Organizational and managerial challenges in the path toward Industry 4.0. *European Journal of Innovation Management, 22*(3), 406 – 421. https://doi.org/10.1108/EJIM-02-2018-0030

Al-Surmi, A., Cao, G., & Duan, Y. (2020). The impact of aligning business, IT, and marketing strategies on firm performance. *Industrial Marketing Management, 84*, 39–49. https://doi.org/10.1016/j.indmarman.2019.04.002

Banerjee, A. (2018). An empirical study to compute the efficiency of Indian banks during the pre and post periods of recession with the help of data envelopment analysis. *Indian Journal of Finance, 12*(4), 37 – 53. https://doi.org/10.17010/ijf/2018/v12i4/122794

Banker, R., Natarajan, R., & Zhang, D. (2019). Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using data envelopment analysis : Second stage OLS versus bootstrap approaches. *European Journal of Operational Research, 278*(2), 368 – 384. https://doi.org/10.1016/j.ejor.2018.10.050

Barasa, L., Vermeulen, P., Knoben, J., Kinyanjui, B., & Kimuyu, P. (2019). Innovation inputs and efficiency : Manufacturing firms in Sub-Saharan Africa. *European Journal of Innovation Management, 22*(1), 59 – 83. https://doi.org/10.1108/EJIM-11-2017-0176

Bellandi, M., & Santini, E. (2019). Territorial servitization and new local productive configurations : The case of the textile industrial district of Prato. *Regional Studies, 53*(3), 356–365. https://doi.org/10.1080/00343404.2018.1474193

Bhullar, A., & Singh, P. (2017). Economic efficiency and growth sustainability of Indian small-scale industries : A pre- and post-liberalization based comparative analysis. *Arthshastra Indian Journal of Economics & Research, 6*(4), 7 – 22. https://doi.org/10.17010/aijer/2017/v6i4/118154

Biener, C., Eling, M., & Wirfs, J. H. (2016). The determinants of efficiency and productivity in the Swiss insurance industry. *European Journal of Operational Research, 248*(2), 703–714. https://doi.org/10.1016/j.ejor.2015.07.055

Bockholt, M. T., Kristensen, J. H., Colli, M., Jensen, P. M., & Wæhrens, B. V. (2020). Exploring factors affecting the financial performance of end-of-life take-back program in a discrete manufacturing context. *Journal of Cleaner Production, 258,* 1 – 9. https://doi.org/10.1016/j.jclepro.2020.120916

Bosman, L., Hartman, N., & Sutherland, J. (2020). How manufacturing firm characteristics can influence decision making for investing in Industry 4.0 technologies. *Journal of Manufacturing Technology Management, 31*(5), 1117 – 1141. https://doi.org/10.1108/JMTM-09-2018-0283

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429 – 444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, P. - H., Ong, C. - F., & Hsu, S. - C. (2016). Understanding the relationships between environmental management practices and financial performances of multinational construction firms. *Journal of Cleaner Production, 139,* 750 – 760. https://doi.org/10.1016/j.jclepro.2016.08.109

Davtalab-Olyaie, M. (2019). A secondary goal in DEA cross-efficiency evaluation: A "one home run is much better than two doubles" criterion. *Journal of the Operational Research Society, 70*(5), 807 – 816. https://doi.org/10.1080/01605682.2018.1457482

Dobos, I., & Vörösmarty, G. (2019). Inventory-related costs in green supplier selection problems with Data Envelopment Analysis (DEA). *International Journal of Production Economics, 209,* 374 – 380. https://doi.org/10.1016/j.ijpe.2018.03.022

FICCI. (2016). *Knowledge paper on global shifts in textile industry & India's position.* TAG 2016, Mumbai. http://ficci.in/spdocument/20817/3-FICCI-TAG-2016-Whitepaper.pdf

Gambhir, D., & Sharma, S. (2015a). Are exporting firms more productive in the Indian textile industry ? *Measuring Business Excellence, 19*(4), 72 – 84. https://doi.org/10.1108/MBE-07-2014-0021

Gambhir, D., & Sharma, S. (2015b). Productivity in Indian manufacturing : Evidence from the textile industry. *Journal of Economic and Administrative Sciences, 31*(2), 71 – 85. https://doi.org/10.1108/JEAS-09-2014-0021

Gupta, G. K., & Khan, M. A. (2017). Exports competitiveness of the Indian textile industry during and after ATC. *Journal of Textile Science & Engineering, 7*(5), 1 – 6. https://doi.org/10.4172/2165-8064.1000313

Gupta, S., & Kumar, S. (2018). Influence of demographic determinants on reverse mortgage willingness : An empirical study from India. *Arthshastra Indian Journal of Economics & Research, 7*(2), 7 – 20. https://doi.org/10.17010/aijer/2018/v7i2/124537

Halkos, G., & Petrou, K. N. (2019). Treating undesirable outputs in DEA : A critical review. *Economic Analysis and Policy, 62,* 97 – 104. https://doi.org/10.1016/j.eap.2019.01.005

Hasanuzzaman, & Bhar, C. (2017). Environmental sustainability : The emerging issues in India's textile sector. *International Journal of Social Ecology and Sustainable Development (IJSESD), 8*(4), 48 – 60. http://doi.org/10.4018/IJSESD.2017100104

Ibrahim, H. I., & Salau, E. S. (2016). Efficiency of village extension agents in Nigeria : Evidence from a data envelopment analysis. *Journal of Agricultural Sciences, 61*(1), 93 – 101. https://doi.org/101.10.2298/JAS1601093I

India Brand Equity Foundation (IBEF). (2018). *Textile industry analysis.* https://www.ibef.org/industry/textiles.aspx

Izadikhah, M., & Farzipoor Saen, R. (2015). A new data envelopment analysis method for ranking decision making units: An application in industrial parks. *Expert Systems, 32*(5), 596–608. https://doi.org/10.1111/exsy.12112

Kang, Y. Q., Xie, B. - C., Wang, J., & Wang, Y. - N. (2018). Environmental assessment and investment strategy for China's manufacturing industry : A non-radial DEA based analysis. *Journal of Cleaner Production, 175,* 501 – 511. https://doi.org/10.1016/j.jclepro.2017.12.043

Kar, B., & Jena, M. K. (2019). Performance and age of companies listed on the Bombay Stock Exchange. *Indian Journal of Finance, 13*(5), 52 – 67. https://doi.org/10.17010/ijf/2019/v13i5/144185

Khurana, A., & Khosla, R. (2019). Economic reforms and cost efficiency in the banking sector in India. *Indian Journal of Finance, 13*(11), 24 – 35. https://doi.org/10.17010/ijf/2019/v13i11/148414

Kuo, R. J., & Lin, Y. J. (2012). Supplier selection using analytic network process and data envelopment analysis. *International Journal of Production Research, 50*(11), 2852–2863. https://doi.org/10.1080/00207543.2011.559487

Liu, H. H., Song, Y. Y., & Yang, G. L. (2019). Cross-efficiency evaluation in data envelopment analysis based on prospect theory. *European Journal of Operational Research, 273*(1), 364–375. https://doi.org/10.1016/j.ejor.2018.07.046

Mathiyazhagan, K., Sengupta, S., & Mathivathanan, D. (2019). Challenges for implementing green concept in sustainable manufacturing : A systematic review. *OPSEARCH, 56*(1), 32–72. https://doi.org/10.1007/s12597-019-00359-2

Mikušová, P. (2015). An application of DEA methodology in efficiency measurement of the Czech public universities. *Procedia Economics and Finance, 25,* 569 – 578. https://doi.org/10.1016/S2212-5671(15)00771-6

Ministry of Textiles, Government of India (MoT GoI). (2018). *Department of Industrial Policy and Promotion, Union Budget 2017–18.* http://texmin.nic.in/sites/default/files/AnnualReport2017-18%28English%29.pdf

Nguyen, T. M., Le, Q. H., Tran, T. V., & Nguyen, M. N. (2019). Ownership, technology gap and technical efficiency of small and medium manufacturing firms in Vietnam : A stochastic meta frontier approach. *Decision Science Letters, 8*(3), 225 – 232. https://doi.org/10.5267/j.dsl.2019.3.002

Patel, M. P., & Ranjith, V. K. (2018). Measuring efficiency and productivity change of multi-specialty private sector hospitals in India : A DEA based Malmquist Productivity Index approach. *Indian Journal of Finance, 12*(5), 25 – 42. https://doi.org/10.17010/ijf/2018/v12i5/123691

Piyathanavong, V., Garza-Reyes, J. A., Kumar, V., Maldonado-Guzmán, G., & Mangla, S. K. (2019). The adoption of operational environmental sustainability approaches in the Thai manufacturing sector. *Journal of Cleaner Production, 220,* 507 – 528. https://doi.org/10.1016/j.jclepro.2019.02.093

Ramanathan, R. (2003). *An introduction to data envelopment analysis : A tool for performance measurement.* Sage.

Rashidi, K., & Cullinane, K. (2019). Evaluating the sustainability of national logistics performance using Data Envelopment Analysis. *Transport Policy, 74,* 35 – 46. https://doi.org/10.1016/j.tranpol.2018.11.014

Raut, R., Gardas, B. B., & Narkhede, B. (2019). Ranking the barriers of sustainable textile and apparel supply chains : An interpretive structural modelling methodology. *Benchmarking : An International Journal, 26*(2), 371 – 394. https://doi.org/10.1108/BIJ-12-2017-0340

Sharma, A., & Narula, S. A. (2020). What motivates and inhibits Indian textile firms to embrace sustainability ? *Asian Journal of Sustainability and Social Responsibility, 5*(1), 1 – 23. https://doi.org/10.1186/s41180-020-0032-8

Textile mills tie up with GEDA to reduce energy consumption. (2018, December 2). *The Times of India.* https://timesofindia.indiatimes.com/city/surat/textile-mills-tie-up-with-geda-to-reduce-energy-consumption/articleshow/66900593.cms

Tran, T. H., Mao, Y., Nathanail, P., Siebers, P. - O., & Robinson, D. (2019). Integrating slacks-based measure of efficiency and super-efficiency in data envelopment analysis. *Omega, 85,* 156–165. https://doi.org/10.1016/j.omega.2018.06.008

Vikas, V., & Bansal, R. (2019). Efficiency evaluation of Indian oil and gas sector : Data envelopment analysis. *International Journal of Emerging Markets, 14*(2), 362–378. https://doi.org/10.1108/IJoEM-01-2018-0016

World Trade Organization. (n.d.). *Textiles.* www.wto.org/english/tratop_e/texti_e/texti_e.htm

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