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Measuring Production Efficiency of Readymade Garment Firms

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ABSTRACT

In the garment industry, performance of a firm is generally measured by using conventional ratios such as number of garments per machine and per operator. These ratios cannot reflect the firm's performance completely as the firm does not use only a single input to produce a single output. In this context, Data Envelopment Analysis (DEA) is an appropriate technique as it considers multiple inputs and outputs to measure the production efficiency of a firm. This paper, therefore, applies this technique to estimate the production efficiency of ready-made garment firms. The study is based on the primary data collected from eight ready-made garment firms located in Bangalore, India. To measure the efficiency, we consider the number of stitching machines and number of operators as input-variables and the number of pieces of garment produced as an output-variable. The DEA results show that under the CRS technology assumption, average production efficiency score in the garment firms works out to be 0.75. This indicates that on an average, the firms could increase their output by 25 percent with the existing level of inputs. When the aggregate production efficiency is decomposed into pure production efficiency and scale efficiency using VRS production function, it is found that on an average, the firms are 17 percent inefficient in pure production efficiency and 9 percent in scale efficiency. Most of the firms are found operating under decreasing return to scale. This indicates that the production efficiency of the firms could be improved by adjusting the plant-size at the optimum level. The study also concludes that the DEA is superior to the ratio analysis for performance evaluation of the garment industry.

Keywords: Readymade Garment firm, Production efficiency, Data Envelopment Analysis, Ratio Analysis

I. Introduction

Measurement of performance of a garment firm in relation to other firms is often carried out in the garment industry through the ratio analysis such as number of garments produced per operator or per machine. Although this technique is simple, the most important drawback is that it is inappropriate in making decisions based on one single ratio when there are many inputs and outputs (Duzakın and Duzakın, 2007). It cannot capture the effects of factors that affect the performance of an organization (Smith, 1990). In practice, no firm uses only a single input to produce a single output. In case of garment industry, machine, operator, raw material, energy, and other inputs are required to produce a garment. In such cases, Data Envelopment Analysis (DEA) is an appropriate tool as it considers multiple inputs and outputs to measure the productivity and efficiency of any decision-making unit.

Among the studies available on garment productivity in India, Khanna (1991), Khanna (1993), Bheda et al. (2001) and Bheda (2002) have used partial factor productivity measure to assess the performance of the firms. Rangrajan (2005) and Joshi et al. (2005) have also used the number of garments per machine and per operator to compare the productivity of Indian garment industry with neighbouring countries. These ratios cannot reflect the overall performance of the garment firm and are unable to compare the efficient firm with the inefficient one. Such studies are of little significance when the objective is to identify and analyze maximally efficient firms in comparison to the less efficient ones.

Earlier studies on the Indian textile industry were carried out by the researchers to assess the performance of individual firms and to compare inter-firm performance. Solankar and Singh (2000) measure the relative efficiency of 40 Indian textile-spinning firms for the period 1997-1998 using DEA-BCC model. Bheda (2002) estimates productivity level of the Indian apparel firms, using partial factor productivity approach. Hashim (2005) analyzes the productivity level and factor price and their influence on unit cost growth in the Indian cotton yarn and garment industries for the selected states using panel data for the period 1989-1997. In this study, he estimates Total Factor Productivity[1] (TFP) by using translog multilateral index. Bhandari and Ray (2007) measure the levels of technical efficiency in the Indian textiles industry at the firm level using DEA. The data used for the study of the firms relate to the production of cotton, woolen, silk, synthetic and other natural fibers. Bhandari and Maiti (2007) use translog stochastic frontier production function (SFPF) to measure the technical efficiency of Indian textile firms. Joshi and Singh (2008) examine the TFP growth in Indian textile industry using Malmquist Productivity Index (MPI).

The review of literature on the subject clearly indicates that there has not been any study conducted so far on the Indian garment industry that has used DEA to measure the production efficiency of individual firms. Keeping this in view, this paper measures the production efficiency of eight readymade garment firms in Bangalore. The paper is structured as follows: Section II deals with the data and variables, Section III describes the models followed by results of the DEA analysis in Section IV and Section V compares the results of DEA with ratio analysis. The findings are discussed in the final section.

II. Data Collection

The study is limited to garment manufacturers that produce homogenous product (i.e, bottoms). The DEA requires that set of the firms being analyzed should be comparable in the sense that each firm utilizes the same type of inputs to produce the same type of outputs (Odeck 2008). As our selected firms are in the same business and produce the same product, the DEA is the most suitable technique to be applied for assessing the relative efficiency of these firms and setting benchmarking for the inefficient firms to improve their performance. Further, the sample of firms is restricted only to the domestic manufacturers as they are under similar market, environmental and infrastructural conditions. Since the study covers only bottom manufacturers, the results may not be directly applicable to manufacturers of other garment products. The sample size is small as some firms did not provide their input-output data and other relevant information. Earlier studies on the Indian garment industry have also suffered due to manufacturers' concern about keeping the information confidential (Bheda et al., 2001; Kalhan, 2008).

Initially, we approached Apparel Export Promotion Council for getting information on garment manufacturers. The data provided by the council contained the addresses and contacts of the manufacturing units. It was difficult to identify the product-wise details of the firms from that information. We sent e-mails with a questionnaire and datasheet to a large number of manufacturers. We did not received any positive response from them. We also tried to contact the garment firms through telephone in Delhi, Mumbai, and Bangalore but failed to get a positive response. Hence, the next choice was to use the secondary databases like PROWESS and Capitaline. These databases contain data on a large number of manufacturing firms, including readymade garments, but these sources have balance sheet-based financial data of individual companies and do not have information about the number of workers and number of machines of garment firms. In India, only Annual Survey of Industry (ASI) provides the data on number of employees at aggregate level i.e. three digit data. It provides the data at firm level without disclosing the identity. However, ASI does not have data on physical output and number of machines of the selected industry. Therefore, in order to estimate the production efficiency, using physical data on workers, machines and output, we attempted to conduct primary data survey of individual firms in Bangalore and got the information only from eight bottoms manufacturing units.

In DEA analysis, results are influenced by the size of the sample. In this case study, the number of garment firms is eight which are consistent with the rule of thumb provided by Banker et al. (1984) that the DMU should be at least twice the sum of input and output (Chu et al., 2008). The sample size in this study is quite similar to the studies of Majumdar (1994).

Selection of Variables

Selection of appropriate input and output variables is an important stage in DEA analysis. A model with a large number of variables is one that may fail to have any discriminatory power between firms because most firms will tend to be rated efficient (Majumdar, 1994). Therefore, input-output variables in DEA analysis should be minimal. We identify the potential input-output variables by reviewing the earlier studies on performance evaluation. Bheda (2002) estimates the productivity of the Indian garment firms using the number of shirts produced as an output and the number of stitching machines and operators used as inputs. Hashim (2005) analyzes the productivity level of Indian textile and garment industries using gross output as an output and employee, material, fuel consumed, and capital as input variables. Singh and Agarwal (2006) examine the TFP growth and its components in the sugar industry of Uttar Pradesh using installed capacity, employee, raw material, fuel as inputs and sugar production as an output. Chien et al. (2007) also use total energy generated as the output factor and total installed capacity (MW), total number of employees, and total production cost as input factors to measure the productivity changes in the Taiwan thermal power plants.

Table 1. Descriptive Statistics of Selected Variables

Variables	Garments/year	Operators	Machines
Mean	417500	358	143
Max	1400000	1500	500
Min	200000	150	75
Std. Dev.	401452	462	144

Table 2. Correlation Matrix and R^2 results of Selected Variables

Correlation Matrix

Variables	Garments/year	Operators	Machines
Garments/year	1		
Operators	0.9908* (0.000)	1	
Machines	0.9952* (0.000)	0.9976* (0.000)	1

Regression Analysis

R^2	Adjusted R^2	F- Value	Significance (error)
0.991	0.987	281	0.000

Note: Figures in parentheses are error levels; * significant at 0.01 error level, n = 8

In the above reviewed studies of different sectors, the number of employees and installed capacity were used as input variables and gross output as an output variable. In our study, the number of stitching machines and the number of operators are selected as input variables; and total pieces of garment produced as an output variable. The production of the garment industry fully depends on the total number of stitching operators and total number of stitching machines. We do not find any difference in the raw material consumption across firms, as most of the firms are using automatic cutters for cutting the fabric. Therefore, there is a minimum wastage of fabric. We also do not find any difference in energy consumption as almost all firms have power driven machines. We find that the electricity consumption per stitching machine is almost equal in the surveyed firms. Hence, we do not consider the raw material consumption and energy consumption as input variables for the study. The descriptive statistics of input-output data are shown in Table 1.

Correlation and adjusted R^2 analyses have been conducted to know the extent of variation in garments produced per year. The results are shown in Table 2, which indicates that the output is significantly correlated with these inputs. About 99 percent of variations in the output variable are explained by these explanatory input variables.

III. Models Used

This paper applies DEA methodology to measure the production efficiency[2] of the garment firms located in Bangalore, India. Using only observed output and input data of the firms, this technique evaluates how efficiently the inputs are converted into outputs. According to literature, there are two broad methodologies for measuring technical efficiency-the econometrically specifying stochastic frontier production function (SFPF) and linear programming based non-parametric DEA methodology. The DEA methodology that we use in this paper has some advantages over the SFPF. First, DEA does not assume any specific functional form for the production function. Second, it does not make a priori distinction between the relative importance of outputs and inputs. Third, it is relatively insensitive to model specification, i.e., the efficiency measurement is similar whether input-orientation or output-orientation is used. However, DEA also has some limitations. Compared with the stochastic frontier method, the main disadvantage of the DEA approach is that it does not provide statistical tests for the estimated production function (Zheng et al., 2003).

DEA technique was first formulated by Charnes, Cooper and Rhodes (CCR) in 1978. In this model, the ratio of the weighted outputs to weighted inputs for each firm being evaluated is maximized (Charnes et al., 1978). It is known as CCR model based on constant returns to scale[3] (CRS). Subsequently, Banker, Charnes and Cooper (1984) proposed another model based on variable return to scale[4] (VRS). In this study, we use both CCR and BCC models. For mathematical details of these models, please see Coelli et al. (1998). Here, we have discussed the input oriented[5] and output oriented[6] models briefly. The following notation is used in the description of various DEA models discussed in this section.

Overview of notations:

x_i = input vector of ith firm

y_i = output vector of ith firm

x_j = input vector of j firms, where $j = 1,2,\ldots\ldots,N$

y_j = output vector of j firms, where $j = 1,2,\ldots\ldots,N$

u = vector of output weights

ν = vector of input weights

θ = efficiency score corresponding to the input oriented models

$1/\phi$ = efficiency score corresponding to the output oriented models

λ = vector of constants

Assume, there are data on K inputs and M outputs for each of N firms. For the ith firm, inputs and outputs are represented by the column vectors x_i and y_i respectively. The KxN input matrix, X, and the MxN output matrix, Y, represent the data for all N firms. Then, the efficiency of a garment firm is defined as the ratio of weighted sum of outputs to weighted sum of inputs $(u' y_i / v' x_i)$. The optimal weights are obtained for the ith firm by solving the mathematical linear programming problem:

$$\begin{aligned} &\max_{u,v} (u' y_i / v' x_i), \\ &s.t. \quad u' y_j / v' x_j \leq 1, \quad j = 1,2,\ldots\ldots,N \\ &\qquad u, v \geq 0 \end{aligned} \tag{1}$$

Solving this LPP allows finding values for u' and ν', such that the efficiency of firm "*i*" is maximized, subject to the restriction that efficiency for the rest of the firms is smaller than or equal to 1. One problem with this particular ratio formulation (1) is that it has infinite solutions.

To avoid this, the next restriction is imposed $v' x_i = 1,$ which provides:

$$
\begin{aligned}
& \max_{u,v}(u' y_i), \\
& s.t. \quad v' x_i = 1, \\
& \qquad u' y_j - v' x_j \le 0, \quad j = 1,2,\ldots\ldots,N \\
& \qquad u, v \ge 0
\end{aligned}
\qquad (2)
$$

The equation (2) is known as multiplier form of DEA. Using the duality in linear programming, the envelopment model can be written as,

$$
\begin{aligned}
& \min_{\theta,\lambda} \theta, \\
& s.t. \quad -y_i + Y\lambda \ge 0, \\
& \qquad \theta x_i - X\lambda \ge 0, \\
& \qquad \lambda \ge 0,
\end{aligned}
\qquad (3)
$$

where θ is a scalar and λ is a Nx1 vector of constants. Equation 2 involves the constraints based on number of firms, on the other hand equation 3 involves the fewer constraints based on the total number of inputs and outputs. Therefore, the envelopment model 3 is generally used based on constant return to scale. The value of θ is the efficiency score of the i^{th} firm. When the firm achieves θ=1, then that firm is technically efficient.

The CRS assumption is only appropriate when all the firms operate at an optimal scale (Coelli et al. 1998). In the garment industry, the restrictions on garment trade under the Multi Fibre Agreement[7] have been removed from 1st January 2005. Specifically, the major markets like USA, Europe and Canada have removed the restrictions for the import of garments from this date and these are the major markets for the Indian textile and clothing industry. From 2001, the restrictions on the investment in plant and machinery[8] in the Indian garment industry have been removed under the National Textile Policy 2000. Now, the major producers have started producing garments on a large scale. Most of the garment firms in India are micro and small-scale. In this scenario, these firms have to compete with the domestic as well as global garment producers. Accordingly, they need to adjust their scale-size of the plant. Hence, to understand whether the inefficiency in the firms is due to inefficient utilization of resources or inappropriate scale-size, we decompose the aggregate technical efficiency into pure technical efficiency and scale efficiency using the BCC model. The BCC model can be written by adding the convexity constraint $N1'\lambda = 1$ in equation (3) which gives the equation;

$$
\begin{aligned}
& \min_{\theta,\lambda} \theta, \\
& s.t. \quad -y_i + Y\lambda \ge 0, \\
& \qquad \theta x_i - X\lambda \ge 0, \\
& \qquad N1'\lambda = 1 \\
& \qquad \lambda \ge 0,
\end{aligned}
\qquad (4)
$$

where, N1 is an Nx1 vector of ones. The above-derived models are input oriented models. In this study, we prefer to apply the output-oriented models because the objective of garment industry is normally to increase outputs rather than to decrease inputs. This industry is an employment generative industry with small investment giving maximum value addition to the textile sector. The industry has upward linkages for the weaving industry. The garment industry consumes 30 to 35 percent of fabrics produced by the weaving industry. Hence, minimization of inputs will affect the entire textile chain. In addition, 70 percent of the garments produced are consumed in the domestic markets and 30 percent are used for export. We, therefore, use the CCR and BCC models with output orientation. The output oriented CCR model is as follows,

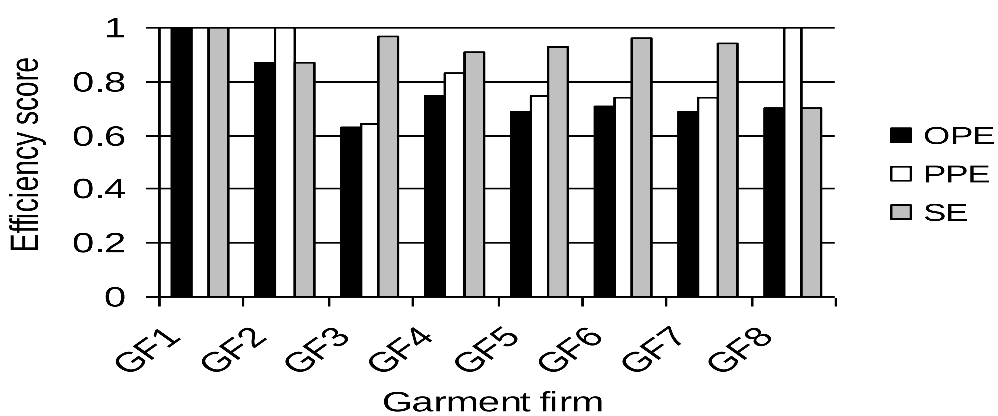
$$\begin{aligned} &\max_{\varphi,\lambda} \phi, \\ &s.t. \quad -\phi y_i + Y\lambda \geq 0, \\ &\qquad x_i - X\lambda \geq 0, \\ &\qquad \lambda \geq 0, \end{aligned} \tag{5}$$

By adding the convexity constraint $N1'\lambda = 1$ in equation (5), the BCC output oriented model is written as,

$$\begin{aligned} &\max_{\varphi,\lambda} \phi, \\ &s.t. \quad -\phi y_i + Y\lambda \geq 0, \\ &\qquad x_i - X\lambda \geq 0, \\ &\qquad N1'\lambda = 1, \\ &\qquad \lambda \geq 0, \end{aligned} \tag{6}$$

where, $1 \leq \phi < \infty$, and $\phi - 1$ is the proportional increase in outputs that could be achieved by the i^{th} firm, with input quantities held constant. Here the $1/\phi$ is the production efficiency of garment firms which varies between zero and one. CCR efficiency is considered as overall production efficiency (OPE) and BCC efficiency as pure production efficiency[9] (PPE). Scale efficiency[10] (SE) is measured as a ratio of CCR efficiency to BCC efficiency.

Figure 1. Overall Production Efficiency, Pure Production Efficiency and Scale Efficiency of the Garment Firms



IV. Results of DEA Analysis

The overall production efficiency, pure production efficiency and the scale efficiency of the individual garment firms are shown in Figure 1. The overall production efficiency scores suggest that a firm is efficient if it scores equal to one under constant return to scale (CRS) technology. It can be observed from the figure that out of eight firms, only one firm

(GF1) turns out technically efficient (OPE=1). The remaining firms are inefficient (OPE<1). For inefficient firms, the CCR and BCC models identify a set of reference efficient firms that can be used as benchmark for them. We have used the reference set[11], peer count[12] and return to scale obtained from the CCR model as shown in Table 3. We find that the average overall production efficiency of the eight apparel firms is 0.75, which indicates that on an average, these firms have to increase output by 25 percent using existing level of inputs.

Table 3. Reference Set, Peer Counts and Return to Scale of Garment Firms

Garment firm	Reference set	Peer Count	Return to scale
GF1	GF1	5	Constant return to scale
GF2	GF2	4	Decreasing return to scale
GF3	GF8, GF 2, GF 1	0	Decreasing return to scale
GF4	GF 8, GF 2, GF 1	0	Decreasing return to scale
GF5	GF 8, GF 2, GF 1	0	Decreasing return to scale
GF6	GF 2, GF 1	0	Decreasing return to scale
GF7	GF 8, GF 1	0	Decreasing return to scale
GF8	GF 8	4	Decreasing return to scale

The BCC model assumes the variable return to scale (VRS) and the measured efficiency is called pure production efficiency (PPE). It indicates how efficiently the inputs are converted into outputs, irrespective of the size of the firm. It is observed from the figure that out of eight garment firms, three are efficient under VRS technology (PPE=1). Average pure production efficiency is 0.83, implying that an individual firm is inefficient in managerial performance by 17 percent. Out of eight firms, GF3 is the most inefficient firm that has scored the lowest score of 0.64. This firm can follow the best practices of firms GF1, GF2 and GF8 for improving its efficiency. It is also observed from the figure that the firm GF2 and GF8 obtain low overall production efficiency, but have 100 percent pure production efficiency. This clearly indicates that these two firms are capable of converting its inputs into output with 100 percent pure production efficiency, but their overall production efficiency is low due to low scale efficiency. This demonstrates that if the effect of scale-size is neutralized, firms GF2 and GF8 can become efficient. Of the eight firms, GF1 positions best practice firm by comprising highest peers count of five in the whole sample. It achieves the most productive scale size (OPE = PPE = SE = 1). Thus, it can be a role model for most of the inefficient firms. Best practices of this firm can be followed as norms or benchmarking by them to monitor their performances.

Table 4. Descriptive Statistics of Efficiency Scores

Variables	Overall production efficiency	Pure Production efficiency	Scale efficiency
Mean	0.75	0.83	0.91
Min	0.63	0.64	0.70
Max	1.00	1.00	1.00
Std. Dev.	0.12	0.14	0.09

The scale efficiency scores of the individual firms are shown in Figure 1. It is observed that out of the eight firms, only one firm (GF1) is scale-efficient. This firm operates at the most productive scale size[13] (MPSS). It is observed from Table 4 that the average scale efficiency is 0.91, which suggests that an average firm may have to correct its scale-size by 9 percent to be scale-efficient. The GF8 has the lowest scale efficiency (SE=0.70) and operates under decreasing return to scale. This firm may decrease its scale-size in order to become efficient under constant return to scale. It is observed from Table 3 that all inefficient firms are operating under decreasing return to scale[14]. This implies that these firms have excess production capacity that could not be utilized efficiently in the year 2008. To sum up, on an average, the selected firms have deficit of 25 percent in overall production efficiency, 17 percent in pure production efficiency and 9 percent in scale efficiency. It is suggested that the garment firms should first give more emphasis on improving the efficiency in converting the inputs into output (PPE) and then on improving the scale efficiency through adjusting the plant-size at the optimum scale.

<u>Target Setting for Inefficient Firms</u>

DEA identifies input and output targets for an inefficient firm to render it relatively efficient. Each of the firms can become efficient by achieving these targets, determined by the efficient reference set for that firm. The inefficient firm can become technically efficient by maximizing the outputs. The actual and target inputs and output are given in Table 5.

Table 5. Actual and Target Inputs/Outputs of the Garment Firms (CCR Model)

	Actual Inputs/Outputs			**Target Inputs/Outputs**		
Firm Codes	**Garments/year**	**Operators**	**Machines**	**Garments/year**	**Operators**	**Machines**
F1	300000	150	75	300000	150	75
GF2	400000	230	120	460000	230	115
GF3	200000	160	80	320000	160	80
GF4	300000	225	100	400000	200	100
GF5	250000	180	90	360000	180	90
GF6	240000	170	90	340000	170	85
GF7	250000	250	90	360000	180	90
GF8	1400000	1500	500	2000000	1000	500
Geom. mean	332999	248	113	445682	223	111

It is observed that except GF1 all remaining firms have to maximize the outputs to operate at the level of the efficient one. For instance, GF7 may have to reduce the number of employee from 250 to 180 and needs to increase the number of garments produced per year from 250000 pieces to 360000 pieces. On an average, the garments firms have to increase the output by 25 percent along with the reduction of 10 percent and 1 percent in operators and machines respectively.

V. Ratio Analysis vs. DEA Analysis

The conventional efficiency measurement in the garment industry considers only a single input and a single output. In case of the garment firm GF8 and GF3 the garments per operator (GPO) are 933 and 1250 respectively as shown in Table 6.

Here, if we compare the firm GF8 with GF3, the firm GF 3 is rated to be more efficient as it produces a higher number of garments per operator per year. This analysis does not take into consideration the other inputs like machine. In order to produce a garment, the firm needs machine, operator, raw material, energy and other inputs. If we consider the other ratio, i.e., garments per machine (GPM), we find that the firm GF8 has a relatively higher productivity (2800 GPM) than that of GF3 (2500 GPM). If we compare the overall production efficiency scores of these two firms, we find that GF8 has a better performance than GF3. Thus, the results based on a single ratio may provide misleading conclusions related to the performances of a firm. In this context, DEA is an appropriate technique, as it considers multiple input-output variables to measure the relative performance of individual firms.

Table 6. DEA efficiency scores and Ratio Analysis Indicators

Garment Firm	DEA Efficiency score	Rank	Garments produced/ operator	Garments produced/ machine
GF1	1	1	2000	4000
GF2	0.87	2	1739	3333
GF3	0.63	8	1250	2500
GF4	0.75	3	1333	3000
GF5	0.69	6	1389	2778
GF6	0.71	4	1412	2667
GF7	0.68	7	1000	2778
GF8	0.70	5	933	2800

VI. Conclusions

This paper estimates the production efficiency of the eight garment firms located in Bangalore, India using the DEA technique. The empirical results suggest that seven out of eight firms are technically inefficient. That is, these firms have not produced the maximum attainable output using the available inputs and technology. On an average, the firms have to increase the actual production of garments by 25 percent to achieve the target outputs. In addition, technical inefficiency has been found due to both inefficient scale-size and resource-utilization. The firms are 25 percent inefficient in overall production efficiency, 17 percent inefficient in pure production efficiency and 9 percent inefficient in scale efficiency. It is suggested that the garment firms should first give more emphasis on improving the efficiency in converting the inputs into output (PPE) and then on improving the scale efficiency through adjusting the plant-size at the optimum scale. Most of the firms are found to operate under the decreasing return to scale. This shows that the firms have the excess production capacity that could not be utilized efficiently in the year 2008.

The DEA gives the overall production efficiency, pure production efficiency, scale-efficiency, benchmarks, and inputs and output targets for the garment firms. On the other side, the usual performance indicators such as the number of garments produced per operator or per machine cannot provide the overall performance evaluation. Therefore, results based on a single ratio may provide misleading conclusions related to the performances of a firm. In this context, DEA is an appropriate technique, as it considers multiple input-output variables to measure the relative performances of individual firms.

VIII. Acknowledgments

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Notes

1. TFP is a ratio of weighted sum of outputs to the weighted sum of inputs over a period.
2. Production efficiency means producing the maximum quantity of output using several inputs. We have used production efficiency as a synonymous word for technical efficiency.
3. Constant returns to scale arises when a proportional increase in the value of all inputs results in the same proportional increase in outputs of the firm.
4. Variable return to scale is defined as the output may change in the increase or decrease in proportion to the change in inputs.
5. The input orientation measures the input quantities, which can be proportionally reduced without changing the output quantities produced.
6. The output orientation measures the output quantities, which can be proportionally expanded without altering the input quantities used.
7. Multi Fibre Agreement was the restrictions on import and export of textile and clothing from 1974 to 1994. The MFA was finally expired in 1994 and phased out in four phases during the period 1995-2004. With the elimination of all remaining quotas in textiles from January 1, 2005, the textile and apparel industries have now fully integrated into the WTO. Now, buyers are thus free to source textile and apparel in any amount from any country. Suppliers are free to export as much as they are able which is subjected only to a system of national tariff.
8. The Indian garment industry was protected for small-scale industry until 2000. There were restrictions on the investment in plant and machinery on large scale in the industry.
9. Pure production efficiency is attributed to efficient conversion of inputs into outputs in which effect of plant-size is neutralized.
10. Scale efficiency is the extent to which a firm can take advantage of return to scale by altering its size towards the optimal scale.
11. A reference set is a set of efficient firms, which acts as a reference point for inefficient firms.
12. Peer count shows how many times an efficient firm has been referred in the reference set of inefficient firms. Best practice firm will have a higher peer count and can be considered as a benchmark for the inefficient firms.
13. Most productive scale size is that size at which a firm obtains 100 percent pure production efficiency and scale efficiency.
14. Decreasing returns to scale exists when output increases less than the proportional increase in the inputs.

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