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Relative Efficiency of Decision Making Units Producing Both Desirable and Undesirable Outputs: A Case of Textile Processing Units in Pakistan

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1. INTRODUCTION

Textile processing is Pakistan's leading industrial manufacturing sub-sector with regard to production, export and labour employment. It produces almost 30 percent of the manufacturing value added, employs 40 percent of the manufacturing sector labour force and represents 63 percent of the total exports of Pakistan. The number of textile processing mills in rural and urban Punjab province and urban Sindh province has grown greatly since the mid-1970s, most of which started operating without proper planning and waste treatment plants, disposing of untreated toxic waste into nearby drains, irrigation canals or rivers. Major textile industrial estates in large cities such as Lahore, Faisalabad, Karachi, and Sialkot contribute 70 percent of the total pollution loads of water bodies.

The textile processing industry in Pakistan, as elsewhere, is characterised by the vast quantity of water consumed and the variety of chemicals used in the process. Liquid wastes from various stages of the operation contain substantial pollution loads in terms of organic matter and suspended material such as fibres and grease. This wastewater is discharged untreated or at the best partially treated, and causes serious environmental impacts on natural water bodies and land in the surrounding area. According to a joint report published by the Pakistan Environmental Protection Agency (PEPA) and Japanese International Cooperation Agency (JICA) 2005, 9000 million gallons of wastewater having 20,000 tons of BOD5 (Biological Oxygen Demand) loading are daily discharged into water bodies from the industrial sector into natural streams, canals, rivers and the sea.

The regulatory system framework for implementation of environmental policy in Pakistan evolved over a period of fifteen years. It began with promulgation of the Pakistan Environmental Protection Ordinance (PEPO) of 1983 (repealed in 1997), notification of NEQS (National Environmental Quality Standards) in 1993 and revision of NEQS in 1999. The NEQS provide for targeted end-of-pipe standards for industrial and municipal effluents for 32 liquid and 16 gaseous parameters. The compliance regime for NEQS was established through the PEPA (Pakistan Environmental Protection Act) 1997.

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This paper is an attempt to measure the relative efficiency of textile processing units in Pakistan using the data envelopment technique. This technique includes measurement of the relative efficiency of any production unit or decision making unit (DMU) that uses multiple inputs and generates multiple outputs, including undesirable outputs (pollutants). The efficiency scores determine the relative efficiency of firms in realising their efforts towards cleaner production and abatement of wastewater pollution discharged into water bodies. A large number of inefficient firms (as found here) implies that pollution control is far from satisfactory.

The following Section 2 provides a brief literature review of the various models and efficiency measurements usually based on the assumption that inputs have to be minimised and outputs have to be maximised. Over the last few years, in a growing number of applications, undesirable outputs (need to be minimised) which are jointly produced with the desirable outputs are incorporated into the production model. The review is followed by Section 3 which is a brief description of methodology of Data Envelopment Analysis (DEA) and its application to textile producing units in Pakistan adopted in this paper. Next, Section 4 deals with the data used in this work and estimation of firms' efficiency scores followed by conclusions in the last Section 5.

2. LITERATURE REVIEW ON DEA AND MODELS WITH UNDESIRABLE OUTPUTS

Data envelopment analysis is a relatively new 'data oriented', non-parametric method of relative efficiency measurement of decision making units (DMUs) which produce multiple desirable and undesirable (pollution) outputs using multiple inputs. DEA uses linear programming to evaluate the relative efficiencies and inefficiencies of peer DMUs. DEA's empirical orientation and absence of *a priori* assumptions have resulted in its use in a number of studies involving efficient frontier estimation. DEA has been applied to a wide range of contexts such as education, health care, transportation and manufacturing [Coelli, *et al.* (2005)].

Farrell (1957) first developed the basic ideas in DEA and applied to empirical data in an attempt to correct deficiencies in productivity indices, leading to the replacement of the concept of productivity with the more general concept of 'relative efficiency'. Building on the evaluation of individual firms by Farrell, a non-parametric method was developed by Charnes, Cooper, and Rhodes (1978, 1981) as DEA. It is basically the extension of single-input and single-output efficiency analysis to multi-input and multi-output situations. Compared to the parametric approach, DEA has no assumptions about functional form. Efficiency of a DMU is determined by relative efficiency scores of other DMUs that lie on or below the efficient frontier. In general terms, DEA is a methodology which is therefore directed to frontiers rather than central tendencies. Charnes, *et al.* (1978), proposed an input oriented mathematical programming DEA model which assumed constant returns to scale. This DEA has since been widely used to measure the performance of various kinds of DMUs. In contrast, Banker, Charnes, and Cooper (1984) developed an output-oriented DEA model, which measures radial efficiency of DMUs, simultaneously constructs the best practice frontier, characterises its shape, assumes variable return to scale and provides a performance evaluation for every observation in the sample. Classical DEA models, such as in Charnes, *et al.* (1994), primarily assume that inputs have to be minimised and outputs have to be maximised. However, in a seminal work Koopmans (1951) had already identified smoke pollution and waste as undesirable outputs generated in the production process that need to be minimised. Fare, *et al.* (1989) implemented the non-parametric approach on a 1976 data set of 30 US mills which use wood pulp and three other inputs in order to produce paper but also four pollutants. Their results exhibit that the performance rankings of DMUs turned out to be very sensitive to whether the undesirable outputs were included. Other studies show similar results [e.g. Pittman (1983); Tyteca (1996, 1997)].

Fare, *et al.* (1996) presented an environmental performance indicator by decomposing overall productivity into an environmental index and a productive efficiency index. They assumed weak disposability for undesirable outputs and used DEA modeling techniques developed previously by Fare, *et al.* (1989). Two data sets were examined using these models for US fossil fuel-fired electric utilities. The ranking of utilities identified using the new model was significantly different to rankings from the traditional model, suggesting that traditional DEA models might not be reliable. As DMUs are responsible for the joint production of bad outputs along with desirable outputs, it makes sense to credit a DMU for its provision of desirable output and to penalise it for its production of emissions when evaluating its performance.

Sieford and Thrall (1990) reviewed the various advantages of non-parametric approaches (including DEA) over parametric approaches. One of the significant benefits of non-parametric approaches is the robustness of linear programming methods used to solve DEA problems. Also additional information and new insights with respect to traditional econometric methods are provided by DEA models. Charnes and Cooper (1985) also indicate that another advantage is the feasibility to include an environmental variable in a DEA-based production model which is neither an economic resource nor a product, but a by-product. Since DEA has proven useful for modelling operational processes for performance evaluation, there are a number of DEA spread sheet models e.g. Zhu (2002) that can be used in performance evaluation of DMUs and benchmarking.

In the framework of DEA, Scheel (2001) adopted various approaches to deal with undesirable outputs which have to be minimised. Seiford and Zhu (2002) have shown that standard DEA model can be used to improve the performance of polluting firms by increasing the desirable outputs and decreasing the undesirable outputs. In recent years, reflection of undesirable outputs in the production process and modelling for efficiency/performance measurement has steadily grown. As emphasised by James (1994), 'environmental performance measurement is here to stay but is still in its early stages', and it is evident that 15 years later James's statement remains valid. Moreover, James and Bennett (1994) indicated that, 'The scale of the challenge is such that even the simplest measures are better than none at all. Immediate actions of almost any kind can signal a serious intent to the world, make some reduction of environmental impacts, reduce the risk of negative reactions by regulators, customers and other stakeholders and provide a platform for further action. The over-riding necessity is to begin the process of using business environ metrics to encourage continuous improvement of corporate environmental performance'. In the present study, a data envelopment analysis method as developed in Sieford and Zhu (2002) is applied to the textile processing firms in Pakistan, in order to determine their relative efficiency by modelling undesirable factors (BOD5, COD) in efficiency evaluation.

3. DATA ENVELOPMENT ANALYSIS (DEA)

DEA entails the use of linear programming methods to build a non-parametric piecewise surface over the data to estimate efficiency measures relative to this surface, the efficient technology or production frontier. The technical efficiency scores of each firm or decision making unit (DMU) relative to the best observed practice can be obtained by applying DEA techniques.

3.1. Modelling Undesirable Outputs in the Efficiency Valuations Using DEA Framework

The DEA frame work has conventionally been applied with the implicit assumption that efficient production provides increase in outputs with increased inputs. In reality this assumption may not hold, although an increase in inputs subsequently provides increased output, efficiency may not necessarily be established due to undesirable by-products. In textile processing, fabric is produced which is marketable output and water polluting factors like BOD and COD are its by-products which need to be reduced to increase the performance of DMU. Tyteca (1997) used models of US fossil fuel-fired electric utilities to obtain the best practice frontier of utilities or DMUs exhibiting the best environmental behaviour. He applied four alternative models which includes three linear programming models with different approaches to incorporate undesirable outputs. Dyson, *et al.* (2001) have also developed various methods of taking undesirable output into account. Scheel (2001) categorised different ways of dealing with undesirable outputs into direct and indirect approaches. The key indirect approaches to deal with undesirable output are as follows:

- Undesirable outputs are considered as inputs.
- To transform undesirable output into desirable output, it is deducted from a large number.
- The inverse of undesirable output is considered as a desirable one.

This paper follows Seiford and Zhu (2002) to estimate the relative efficiency of textile processing units (DMUs) in Pakistan. Textile processing involves use of chemicals, bleach and dyes to print fabrics which results in high levels of water polluting factors as undesirable by-products like BOD (Biological Oxygen Demand) and COD (Chemical Oxygen Demand). This results in inefficient production and undesirable outputs which needs to be reduced to improve the efficiency and performance of DMUs. Seiford and Zhu (2002) use classification invariant property to justify the application of a standard DEA model that can be employed to improve the performance by increasing the desirable outputs and decreasing the undesirable outputs. This approach can also be applied in certain conditions such as a water pollution treatment plant, where increase in inputs can lead to improved performance. An important feature of the method is that it adopts and preserves the linearity and convexity of DEA.

3.2. Envelopment Models

The input oriented VRS envelopment model where the inputs are minimised and outputs are kept at their current levels is written as:

$$\theta = \min \theta$$

subject to

$$\begin{aligned} &\textstyle\sum_{j=1}^{n} \lambda j\, xij \le \theta xio && i = 1,2,\ldots,m; \\ &\textstyle\sum \lambda j\, yrj \ge yro && r = 1,2,\ldots,s; \\ &\textstyle\sum \lambda j = 1 \\ &\lambda j \ge 0 && j = 1,2,\ldots,n; \end{aligned} \qquad \ldots \ldots \ldots \ldots (1)$$

where as here *DMUo* represents one of the *n DMUs* under evaluation and *xio* and *yro* are the *i*th input and *r*th output for *DMUo* respectively. Since $\theta = 1$ is a feasible solution to (1), the optimal value to (1) $\theta^* \le 1$. If $\theta = 1$ then the current input levels cannot be reduced (proportionally), indicating that DMUo is on the frontier. Otherwise, if $\theta^* < 1$ then DMUo is dominated by the frontier. θ^*represents the efficiency score (input-oriented) of DMUo.

$$\min \theta - \varepsilon \left(\textstyle\sum s_i^{-} + \sum sr^{+}\right)$$

subject to

$$\begin{aligned} &\textstyle\sum_{j=1}^{n} \lambda j\, xij + si^{-} = \theta\, xio && i = 1,2,\ldots,m; \\ &\textstyle\sum \lambda j\, yrj - sr^{+} = yro && = 1,2,\ldots,s; \\ &\textstyle\sum \lambda j = 1 \\ &\lambda j \ge 0 && j = 1,2,\ldots,n; \end{aligned} \qquad \ldots \ldots \ldots \ldots \ldots (2)$$

The output oriented VRS envelopment model can be expressed as:

$$\max \phi - \varepsilon \left(\textstyle\sum si^{-} + \sum sr^{+}\right)$$

subject to

$$\begin{aligned} &\textstyle\sum \lambda_j\, xij + si^{-} = \bar{x}io && i = 1,2,\ldots,m; \\ &\textstyle\sum \lambda_j\, yrj - sr^{+} = \phi\, \bar{y}ro && r = 1,2,\ldots,s; \\ &\textstyle\sum \lambda j = 1 \\ &\lambda j \ge 0 && j = 1,2,\ldots,n; \end{aligned} \qquad \ldots \ldots \ldots \ldots (3)$$

ϕ^* represents the efficiency score (output-oriented) of DMUo. The above model can be calculated in a two stage process. ϕ^* is first calculated by ignoring the slacks and then optimise the slacks by fixing the ϕ^* in the following linear programming problem.

$$\max \textstyle\sum s_i^{-} + \sum s_r^{+}$$

subject to

$$\begin{aligned} &\textstyle\sum_{j=1}^{n} \lambda j\, xij + s_i^{-} = xio && i = 1,2,\ldots,m; \\ &\textstyle\sum \lambda_j\, yr_j - sr^{+} = \phi^*\, yro && = 1,2,\ldots,s; \end{aligned} \qquad \ldots \ldots \ldots \ldots (4)$$

$$\sum \lambda j = 1$$
$$\lambda j \geq 0 \qquad j = 1,2,\ldots,n;$$

DMUo is efficient if and only if $\phi^* = 1$ and $s_i^{-*} = s_r^{+} = 0$ for all i and r. We can get the slacks through

$$si^{-} = x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i = 1,2,\ldots, m; \qquad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5)$$
$$sr^{+} = \sum \lambda_j y_{rj} - \phi^* y_{ro} \qquad r = 1,2,\ldots,s;$$

It is to be noted that $\phi^* \geq 1$ and $\phi^* = 1$ if and only if $\theta^* = 1$. This indicates that model 1 and model 3 above identify the same frontier.

3.3. Efficiency Invariance

Suppose that inputs and outputs are transformed to $\bar{x}_{ij} = x_{ij} + u_i$ and $\bar{y}_{rj} = y_{rj} + v_r$, where u_i and v_r are nonnegative. Then the input-oriented VRS model become

$$\min \theta - \varepsilon (\sum s_i^{-} + \sum s_r^{+})$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{-} = \theta \bar{x}_{io} \qquad i = 1,2,\ldots,m;$$
$$\sum \lambda_j y_{rj} - s_r^{+} = \bar{y}_{ro} \qquad r = 1,2,\ldots,s; \qquad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (6)$$
$$\sum \lambda_j = 1$$
$$\lambda_j \geq 0 \qquad j = 1,2,\ldots,n;$$

and output–oriented VRS model become

$$\max \phi - \varepsilon (\sum s_i^{-} + \sum s_r^{+})$$

subject to

$$\sum \lambda_j x_{ij} + s_i^{-} = \bar{x}_{io} \qquad i = 1,2,\ldots,m;$$
$$\sum \lambda_j y_{rj} - s_r^{+} = \phi \bar{y}_{ro} \qquad r = 1,2,\ldots,s; \qquad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (7)$$
$$\sum \lambda_j = 1$$
$$\lambda j \geq 0 \qquad j = 1,2,\ldots,n;$$

Generally, there are three categories of invariance under data transformation in DEA. The first one is "classification invariance" where the classifications of efficiencies and inefficiencies are invariant to the data transformation. The second category is the "ordering invariance" of the inefficient DMUs. The third one is the "solution invariance" in which the new DEA model after data transformation must be equivalent to the old one that is both mathematical programming problems must have exactly the same solution. Seiford and Zhu (2002) deal only with the classification invariance.

3.4. Undesirable Outputs in DEA

y^g_{rj} and y^b_{rj} denote the desirable or good and undesirable or bad outputs, respectively. We always want to increase y^g_{rj} and decrease y^b_{rj} to improve the performance of a DMU. However in the output-oriented VRS envelopment model which is the standard BCC model, both y^g_{rj} and y^b_{rj} are supposed to increase to improve the performance. To get the level of desirable outputs increased and to decrease the undesirable outputs following approach is adopted.

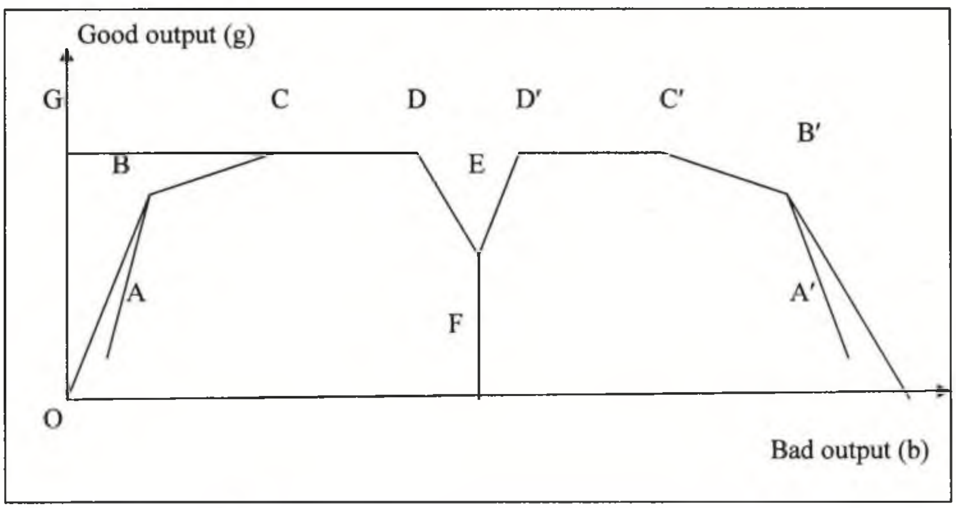
Each undesirable output is first multiplied by "–1" and then find a proper value v_r to let all negative undesirable outputs be positive. That is, $\bar{y}^b_{rj} = -y^b_{rj} + v_r = 0$. This can be achieved by $v_r = \max j \{y^b_{rj}\} + 1$, for example. Based upon (7) we have

max h

subject to

$$
\begin{aligned}
&\textstyle\sum_{j=1}^{n} \lambda_j y^g_{rj} \geq h y^g_{ro} \\
&\textstyle\sum \lambda_j \bar{y}^b_{rj} \geq h \bar{y}^g_{ro} \qquad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (8)\\
&\textstyle\sum \lambda_j x_{ij} \leq x_{io} \\
&\lambda_j \geq 0, \; j = 1,\ldots,n
\end{aligned}
$$

It should be noted that (8) increases desirable outputs and decreases undesirable outputs.



Adapted from Seiford and Zhu (2002).

Fig. 1. Treatment of Bad Outputs

Figure 1 illustrates three approaches for treating the undesirable outputs. The input used by five DMUs (A, B, C, D and E) is equal to produce one desirable output (g) and one undesirable output (b). First, under the output oriented BCC model (25), the area OGCDEF is the conventional output set. If we treat the undesirable output as (b) an input, then ABCD becomes the BCC frontier. For the proper translation vector, we can rotate the output set at EF and obtain the symmetrical region. In this case, DMUs A′, B′, and C′, which are, respectively, the adapted points of A, B and C, are efficient. Adapting from Seiford and Zhu (2002), the envelopment model is applied in this paper with variable returns to scale (VRS) to the data of inputs and outputs for the year 2008 from textile processing units in Pakistan. The water pollution indicators, BOD5 and COD are taken as undesirable outputs, as commonly done in literature. This approach is mainly based on the use of DEA classification invariance under which classifications of efficiencies and inefficiencies are invariant to the data transformation. There are different possibilities to treat the undesirable outputs in the DEA-BCC framework. Here, three different approaches to deal with the undesirable outputs are being followed. First, the undesirable outputs are ignored. Second a linear monotone decreasing transformation is applied to the undesirable outputs and then adapted variables are viewed as outputs. Third, the undesirable outputs are treated as inputs.

4. DATA FOR ESTIMATION AND EFFICIENCY SCORES

The data set used in the estimation of efficiency consists of data from the year 2008 for 45 textile processing mills located in the vicinity of the Malir and Lyari rivers, which run across the Karachi industrial area and finally enter the Arabian Sea. The data were collected using a structured questionnaire for a field survey of textile processing mills. All textile processing units or DMUs have similar characteristics in terms of technology for both the production of fabric and waste treatment. The production process produces a desirable output (printed fabric) together with undesirable outputs like water pollutants: BOD5 and COD. Textile processing mills use capital, labour, fuel, raw material and chemicals as inputs to produce the printed fabrics. The quantity of these inputs, the desirable output and the undesirable outputs (BOD and COD) taken as average value for the year 2008, are shown in Table 1.

Table 1

Descriptive Statistics (Sample Size = 45)

Variable	Description	Units	Mean	Std. Dev	Minimum	Maximum
LABR	Labour employed	No. of persons/year	2596	950.53	1006	4521
MATINP	Grey cloth / Chemicals	Rupee value in millions	1629	4531.3	827.51	12576
FUEL	Power and Gas	Rupee value in '000'	6112	1987.01	2844	10943
CAPT	Total Capital	Rupee value in millions	2674.63	4292.9	1603.32	9224.82
Y (Output)	Printed Fabric	yards	33077976	9668818	12758749	51098874
BOD_5	Pollutant	mg / l	346.27	115.51	140	581
COD	Pollutant	mg / l	1250.73	750.45	329	2884

The water polluting firms in the industrial sector of Pakistan are required to meet the liquid effluent standards set for the pollutants (80mg/l for BOD and 150mg/l for COD) by the Pakistan EPA. Command-and-Control regulatory instruments are used to make firms comply with the standards. Very few firms in the sample have effluent treatment plants but some firms, as reported, are using process changes in production and input choices to achieve the effluent standards.

4.1. Estimation of Firms' Efficiency Scores

The efficiency scores of all DMUs are estimated by applying different quantitative models for performance evaluation and benchmarking. DEA Frontier software developed by Zhu (2008) uses Excel solver and does not set any limits on inputs and outputs. These are basically spread sheet models for the output oriented VRS envelopment model and undesirable measure model which are being applied to get estimations of efficiency scores. Table 2 gives the efficiency measures for each DMU or textile processing unit.

Table 2

Efficiency Scores of 45 Textile Processing Units

DMU	Model I	Model II	Model III
1	1.106701	1.039566	1.014200
2	1.139328	1.009178	1.000000
3	1.132166	1.094247	1.085104
4	1.179916	1.177310	1.179916
5	**1.000000**	**1.000000**	**1.000000**
6	**1.000000**	**1.000000**	**1.000000**
7	1.049286	1.049285	1.049286
8	1.037722	1.025142	1.013967
9	**1.000000**	**1.000000**	**1.000000**
10	**1.000000**	**1.000000**	**1.000000**
11	**1.000000**	**1.000000**	**1.000000**
12	1.125148	1.049618	1.038030
13	1.220981	**1.000000**	**1.000000**
14	**1.000000**	**1.000000**	**1.000000**
15	1.265766	1.095057	1.049963
16	1.210730	1.150288	1.120810
17	1.432088	1.189601	1.193484
18	1.167627	**1.000000**	**1.000000**
19	**1.000000**	**1.000000**	**1.000000**
20	**1.000000**	**1.000000**	**1.000000**
21	**1.000000**	**1.000000**	**1.000000**
22	1.004653	1.004653	1.004653
23	1.095247	1.081207	1.070313
24	1.018209	1.018209	1.018209
25	**1.000000**	**1.000000**	**1.000000**
26	1.405910	1.203907	1.279710
27	1.312115	1.136050	1.141400
28	1.219111	1.026875	1.032218
29	1.390636	1.181342	1.192111
30	1.107591	1.000000	1.000000
31	1.416295	1.243812	1.261432
32	**1.000000**	**1.000000**	**1.000000**
33	1.058579	1.050387	1.049436
34	**1.000000**	**1.000000**	**1.000000**
35	1.070015	1.023394	1.000000
36	1.153019	1.066987	1.021070
37	1.216947	1.094275	1.039358
38	1.318040	1.079603	1.026924
39	1.086955	1.003116	**1.000000**
40	**1.000000**	**1.000000**	**1.000000**
41	1.128723	**1.000000**	**1.000000**
42	1.298825	1.052930	1.011868
43	1.163383	**1.000000**	**1.000000**
44	1.412412	1.136864	1.084632
45	1.116544	**1.000000**	**1.000000**

Model I depicts the efficiency value or optimal value to the model when the undesirable outputs are ignored. The only output used in this model is printed fabric as a desirable output and pollutants, BOD and COD are not included. Model 1 shows that there are 13 efficient DMUs and the remaining 32 are inefficient when we ignore the undesirable output in the production process. The DEA model used for estimation of efficiency scores of DMUs (textile processing mills) is DEA classification invariance under which classifications of efficiencies and inefficiencies are invariant to the data transformation. The efficiency scores of DMUs obtained from Model II with the translation vector for increase in desirable output and decrease in undesirable outputs; show that 19 DMUs are efficient as compared to 13 in Model I. This clearly indicates that some producers do give consideration to the reduction in undesirable outputs or behave in socially desirable ways. It is also possible that some of the government environmental policies such as compliance to the national environmental quality standards are being followed by some DMUs which allocate some inputs for pollution control activities. As the second column in Table 2 indicates, most of the inefficient units Model I are less efficient compared to units in Model II. While several DMUs in Model II are inefficient, they are still producing under some pollution control policy or constraint. These results confirm the findings of Fare, *et al.* (1989) and Seiford and Zhu (2002). Figure 2 shows the efficiency scores of DMUs Model II, as this model provides the more realistic scores to reveal the performance of DMUs with respect to performance measurement.

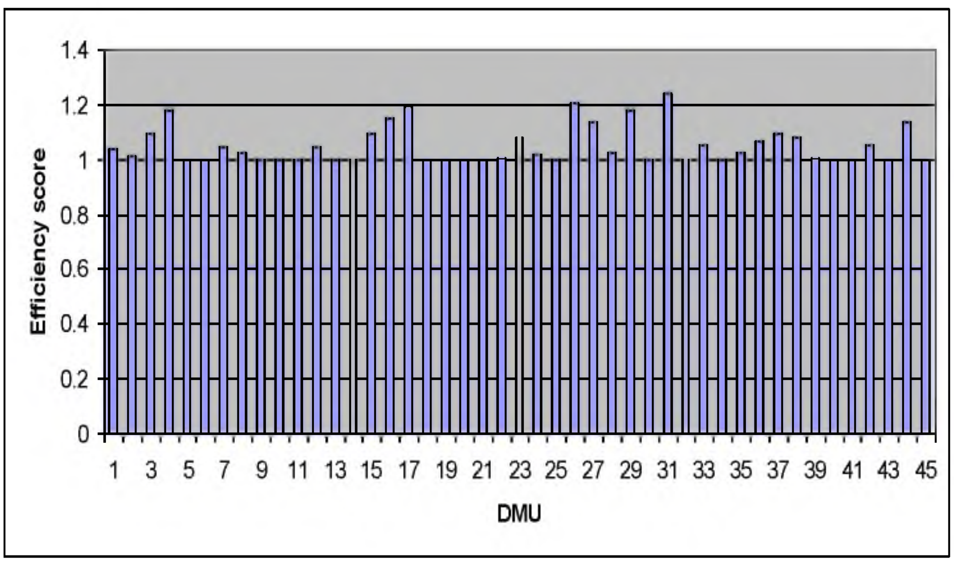


Fig. 2. Estimated Efficiency Scores of Model II across DMUs

Model III gives the efficiency scores of DMUs when both undesirable outputs are treated as inputs. Although this does not reflect the reality of the production process, the results indicate that minimisation of inputs leads to better performance in terms of pollution abatement. However, from the efficiency scores of textile processing units in Pakistan, it is clearly evident that the majority of units in the textile processing industry are not very concerned about water pollution abatement. Existing government policies to control pollution are obviously not as effective as to make all producers comply with the environmental quality standards.

4.3. Constant Returns to Scale vs. Variable Returns to Scale in DEA

The concept of returns to scale is that it relates to the average product. Fried, *et al.* (2008) have explicitly dealt with the concept of returns to scale in production. An average product in a single input/single output case can be readily defined. Let a production unit have input level x and output y, then its average product is y/x. Returns to scale relate to how under efficient operation, average product would be effected by scale size. If the operation is not efficient, then changes in average product as scale size changes can be due both to changes in efficiency and to changes in scale size and it would not be possible to differentiate between the two.

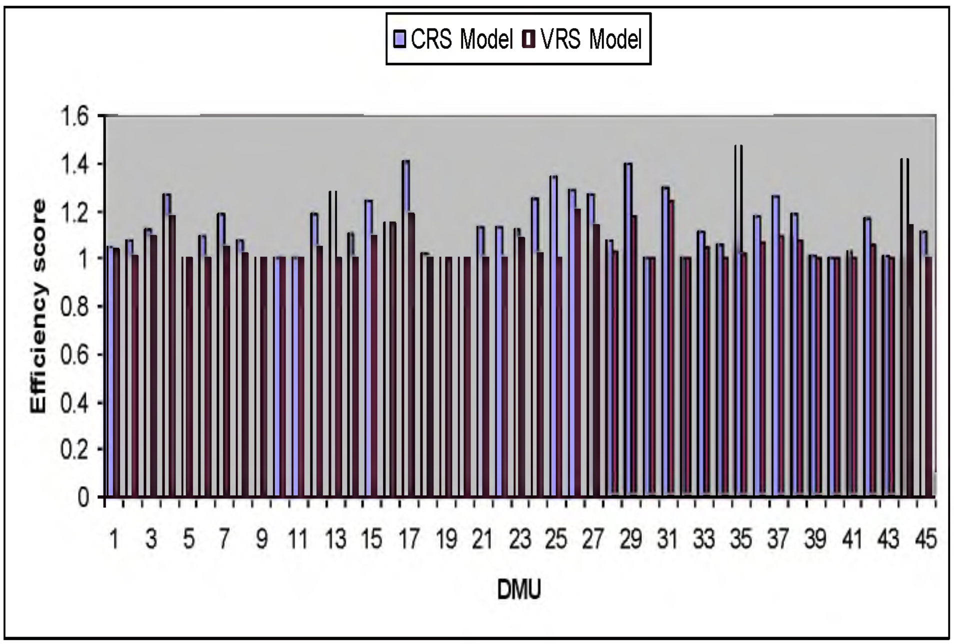


Fig. 3. Efficiency Scores of CRS Model and VRS Model

The estimated efficiency scores of textile processing mills using CRS model and VRS model, presented in Table 3 are shown in Figure 3. The efficiency scores for CRS model are higher than VRS model for all mills. The results in Table 3 are consistent with the findings of Ahn, Charnes, and Cooper (1989) in that a point found to be efficient for the CCR Model (with constant returns to scale constraint) will also be efficient for the BCC model (with variable returns to scale assumption) whereas the converse is not necessarily true. All efficient DMUs 5, 9, 10, 11, 19, 20, 30, 32 and 40 in the CRS column are also efficient in the VRS column, but DMUs number 6, 13, 14, 18, 21, 25, 34, 41, 43 and 45 are only efficient in the VRS column.

Table 3

Comparison of Efficiency Scores of CRS and VRS Models

DMU	CRS Model	VRS Model
1	1.04571	1.03956
2	1.07453	1.00917
3	1.12252	1.09424
4	1.26693	1.17731
5	**1.00000**	**1.00000**
6	1.09543	1.00000
7	1.18620	1.04928
8	1.07932	1.02514
9	**1.00000**	**1.00000**
10	**1.00000**	**1.00000**
11	**1.00000**	**1.00000**
12	1.18512	1.04961
13	1.28079	**1.00000**
14	1.10313	**1.00000**
15	1.24596	1.09505
16	1.15385	1.15028
17	1.40600	1.18960
18	1.02222	**1.00000**
19	**1.00000**	**1.00000**
20	**1.00000**	**1.00000**
21	1.13111	**1.00000**
22	1.12992	1.00465
23	1.11893	1.08120
24	1.25383	1.01820
25	1.34005	**1.00000**
26	1.28425	1.20390
27	1.26527	1.13605
28	1.07693	1.02687
29	1.39663	1.18134
30	1.00000	**1.00000**
31	1.29827	1.24381
32	**1.00000**	**1.00000**
33	1.11196	1.05038
34	1.05719	**1.00000**
35	1.47297	1.02339
36	1.17814	1.06698
37	1.26378	1.09427
38	1.18418	1.07960
39	1.01387	1.00311
40	**1.00000**	**1.00000**
41	1.02631	**1.00000**
42	1.17024	1.05293
43	1.01353	**1.00000**
44	1.41978	1.13686
45	1.11100	**1.00000**

5. CONCLUSIONS

This paper estimates the relative efficiency of production of highly water polluting industry in Pakistan that is textile processing industry. Theoretical aspects of data envelopment analysis technique are being discussed which is employed to measure the relative efficiency of decision making units that uses several inputs to produce desirable and undesirable outputs. Modelling undesirable outputs in the efficiency valuations using the DEA framework is a comparatively new approach in the literature using the classification invariance property. In the context of BCC model, the classification invariance property is used and a linear monotonic decreasing transformation is applied to treat the undesirable outputs so that the output-oriented BCC model permits the expansion of desirable outputs and the contraction of undesirable outputs. Data on the inputs and outputs, including undesirable outputs, from 45 textile processing units in Pakistan for the year 2008 are used to empirically test three different models of efficiency measurement. The results of the analysis are consistent with those found in other studies. The efficiency scores of individual manufacturing firms confirm the fact that some of the producers are showing environmental consciousness may be due to regulatory measures in place but overall the situation is far from satisfactory. Effective measures and instruments are still needed to check the rising pollution levels in water resources discharged by textile processing industry of the country.

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