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MEASURING EFFICIENCY OF MANUFACTURING INDUSTRIES IN PAKISTAN: An Application of DEA Double Bootstrap Technique

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Abstract. This is the very first study, which analyzes technical efficiency and its sources for the large scale manufacturing industries (LSMI) of Pakistan through DEA double bootstrap technique. First, we applied bootstrapped DEA technique for measuring bias-corrected technical efficiency scores by utilizing four inputs and one output. Finally, we employed the bootstrapped truncated regression model for determining the sources of technical efficiency. It is found that industries should reduce their size as there is evidence of diseconomies of scale in our results. Average wage as a measure of workers skill level has positive impact on technical efficiency. Finally market size does not have any significant impact in regression analysis.

Keywords: Technical efficiency, Large scale manufacturing industries (LSMI), DEA double bootstrap, Truncated regression, Pakistan

JEL classification: O14; H21; D61

I. INTRODUCTION

In today's world the globe consists of the borderless economy and each and every entity should be prepared to accept the challenges of this change if they want to play a major role in businesses and remain competitive. An

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entity must be efficient if it wants to stay in businesses. So the performance measurement is necessary for this purpose as the efficiency is the only criteria for organizations to remain in business. It is essential for firms, organizations or industries to reach at their optimal level in order to compete with their business competitors all over the world. It is the requirement of every country to see that its organizational performance is good with high efficiency and productivity in order to achieve its targets. Traditional measures of performance are sales, worker turnover, share prices and exports etc. However, these measures do not reflect the complete picture of a firm's performance. In contrast to these measures, efficiency is a more comprehensive measure as it is based on both the inputs and outputs.

Our study is the first one that analyzes efficiency of large scale manufacturing industries using two-stage bootstrapping technique. Basically, performance measurement is to compare the efficiency of different units, compare the present level of efficiency to previous level of efficiency, comparison of actual efficiency scores to planned efficiency levels, comparison of different geographical zones or performance can be measured by comparing the efficiency of entities functioning under the similar conditions (Wholey & Hatry, 1992). The common criteria for measuring technical efficiency (TE) are to maximize output or profit and minimize the cost. Under certain circumstances, TE is determined as the skill of an industry to produce. An organization or industry is considered as technically efficient if it is producing maximum output from a specific amount of inputs or it is producing a given amount of output by using the minimum amount of inputs. The aim of the producers is to minimize the wastages.

Measuring efficiency is one of the main aspects of today's world. Every entity is curious about its performance and is afraid of failure which may not only harm the industry's reputation but may also shake the investors' confidence in management. Performance evaluation has two basic features: i) it shows the effect of past decisions, and ii) it shows the formation of financial structure of any firm or industry. It is well known that basic purpose of efficiency evaluation is to determine whether industries are employing their resources in the most efficient way (Duzakin and Duzakin 2007). Performance is not a simple concept but it is relatively close to productivity and efficiency. The concept of efficiency indicates that a firm or industry can produce by utilizing the minimum resources or inputs like capital, labor and other expected inputs and is able to remain competitive over the long period of time (Mayes et al., 1994).

Different researchers have defined efficiency in different ways as

Koopmans (1951) defines TE as "There is a possible point in the commodity space which is known as efficient point whenever an increase in one of its coordinates (the net output of one kind) can be obtained only at the expense of decline in some other coordinates (the net output of other kind)". Another definition of efficiency involves equating the inputs and outputs of an organization with that of its peers which are performing well. These peers are estimated in relation to the specific objective where it can be measured based on the output maximization, profit maximization or cost minimization (Thanassoulis, 2001).

The concept of measuring efficiency of producing units was initiated by Farrell (1957). There are two basic techniques which can be used for measuring efficiency; parametric and non-parametric. Aigner et al. (1977), and Meeusen and Broeck (1977) developed the parametric approach (stochastic frontier analysis, SFA) first. Linear programming models, which are also known as non-parametric approach, of Charnes et al. (1978) and Fare et al. (1985) which are based on convexity assumption are famous with the name of data envelopment analysis (DEA). Both approaches have some limitations: SFA necessarily requires specification of functional form and assumptions regarding distribution of the error term. In contrast, DEA does not require these conditions. It is assumed in DEA that decision making units (DMUs), which are producers (economic agents), have control over the discretionary variables but Ouellette and Vierstraete (2004) and many others have justified that non-discretionary inputs are also present in every sector and therefore, these environmental variables must be used in DEA model.

Simar and Wilson (2007) show that earlier studies that involved models such as DEA based on two-stages of production processes were defective due to their failure in describing the data generating process (DGP). Therefore, these approaches are invalid due to the presence of serial correlation in the estimated efficiency scores. The authors identified many problems of these approaches which combine DEA with Tobit regression models. Therefore, they introduced DEA double-bootstrap approach. This approach enables construction of confidence intervals for estimated efficiency scores and let identify its determinants.

The present study is aimed to evaluate the technical efficiency (TE) of large scale manufacturing industries (LSMI) of Pakistan. LSMI are chosen because it is the major part of the industrial sector which has much importance in Pakistan. Industrial sector is the third largest sector after services and agriculture sectors. Manufacturing sector contributes 13.5% of Gross Domestic Product (GDP) and absorbs 14.1 percent of total employed labor force. The productivity and performance of LSMI sector has much importance for sustained growth and development of the country as LSMI comprises more than fifty percent of the industrial sector.

However, it is not sufficient to measure the technical efficiency only without determining its sources. This study measures efficiency scores of LSMI and also assesses its determinants as Pakistan is ranked 133 among 148 in global competitiveness index (the Global Competitiveness Report 2013-14; Schwab (2014)). There is no study in Pakistan that has estimated bias-corrected efficiency scores of manufacturing sector and assessed its sources. This will be the first study to evaluate the technical efficiency and its determinants by applying the DEA double bootstrap. In this study industries are also regrouped for making them comparable.

The remaining of the study is ordered as follows: Review of literature is given in section 2. Section 3 provides methodological framework and describes sources of data. Empirical results of manufacturing industries are interpreted in Section 4. Section 5 consists of conclusions and policy recommendations.

II. REVIEW OF LITERATURE

Many studies have been done for measuring the performance of industries. But almost every study adopted the common technique of DEA (especially in case of Pakistan) for measuring the efficiency of different sectors including manufacturing sector. First, we review the literature related to efficiency, then related to Pakistan.

LITERATURE RELATED TO EFFICIENCY

Mahadevan (2002) analyzed the performance of productivity growth of 28 manufacturing industries of Malaysia over the period of 1981 to 1996. He applied the data envelopment analysis (DEA) to compute Malmquist index of total factor productivity (TFP) growth and technical change, change in technical efficiency and change in scale efficiency were decomposed from Malmquist index. They used three variables (capital, labor as inputs and value added as output). They found that the non-ferrous metal industry obtained the highest TFP growth i.e. 3.7 percent and petroleum refineries obtained the lowest TFP growth i.e. -0.3 percent. They also found that the average weighted TFP growth was 0.8 percent; technical change was 0.3 percent; technical efficiency change was 0.5 percent; pure technical efficiency change was 0.4 percent and scale efficiency change was 0.1 percent. They argued that low TFP growth was due to the small gains in both technical change and technical efficiency, with industries operating close to optimum scale.

Baten et al. (2006) analyzed the technical efficiency of selected manufacturing industries of Bangladesh by applying the stochastic frontier production approach over the period from 1981/1982 to 1999/2000. They covered the selected 3-digit census factories. They included three variables (value added, capital and labor) in their research. They applied two alternative distributions to model the: the truncated normal distribution and the half normal distribution. They found that estimated technical efficiency for selected industries was 40.22% of potential output under the truncated normal distribution while it was 55.57% of potential output for the half normal distribution. They also examined that the time-varying inefficiency parameter was positive which indicated that the technical efficiency declined over the mentioned period of time.

Duzakin and Duzakin (2007) examined the performance of 480 manufacturing firms related to 12 industries of Turkey for the year 2003. Output oriented super slacks based model of data envelopment analysis was applied under constant returns to scale (CRS) assumption. They used two inputs (net assets and average number of employees) and three outputs (profit before taxes, export revenues and gross value added). They found that standard deviation average scores deviated from 0.178 to 0.989 and they found that 278 firms remained below average results, and only 65 firms were identified as efficient. It was examined that the major factor of the inefficiency in leading firms of Turkey was the lack of insufficient level of exports.

Watanabe and Tanaka (2007) examined the efficiency of Chinese industries over the 1994 to 2002 period at province level. They chose the directional output distance function for estimating the two efficiency measures of Chinese industries, one was traditional that considered only desirable output while the other considered desirable and undesirable outputs. They used capital, labor and materials (coal) as inputs while industrial products as desirable output and sulfur dioxide as undesirable output. They found that if the only desirable output is included then the efficiency level was biased. They concluded that neglecting the undesirable output tends to lead to an overestimate of industrial efficiency levels in Shandong, Sichuan, and Hubei. They also found that a province’s industrial structure has significant effects on its efficiency levels.

Ahmadi and Ahmadi (2012) examined the technical efficiency level of manufacturing industries in Iran during 2005 to 2007. They included 23 industries from (2-digit ISIC groups) industries and country's provinces, using output-oriented approach. They measured the relative efficiency with Data Envelopment Analysis. Their results showed that according to CCR model mean values have approximately downward trend while according to BCC model nine industries had lower unit efficiency in constant returns to scale. Technical efficiency had upward trend among provinces. In nutshell, there were only three principal manufacturing industries and two provinces which were identified as the best performers, namely tobacco, transport equipment and coal, and coke. Among thirty provinces, Bushehr and North Khorasan provinces showed the best performance. They also found that scale inefficiency was the most important drawback of industrial firms in Iran.

Ramli and Munisamy (2013) examined the technical efficiency and eco-efficiency of the manufacturing industries in 15 states throughout Malaysia for the period 2001-2010. They applied two approaches i.e. Data Envelopment Analysis (DEA) and Directional Distance Function (DDF). They used two inputs (operating expenditure and capital) and two outputs (one was the desirable output i.e. sales, and the second was undesirable output i.e. CO_2 emission). They found that, under free industrial zone (FIZ), in DEA average technical efficiency deviated from 83% to 92%, and under non-industrial free zone (NFIZ), average technical efficiency varied from 77% to 90%. They analyzed that in DDF while incorporating the desirable and undesirable outputs, under FIZ, average eco-efficiency deviated from 88% to 92% and they found that under NFIZ average eco-efficiency varied from 87% to 90%. They argued that this high eco-efficiency under FIZ for the manufacturing sector demonstrated that environmental performance in Malaysia was not adversely affected with respect to industrial development.

LITERATURE RELATED TO PAKISTAN

Din et al. (2007) analyzed TE of large scale manufacturing sector of Pakistan. They used DEA approach under constant returns to scale (CRS) and variable returns to scale (VRS) assumption. Data were collected from 101 industries for 1995-96 and 2000-01. Input variables included capital, labor, industrial cost and non-industrial cost and output variable was contribution to GDP. Under CRS, the results indicated that mean efficiency has improved from 0.23 in 1995-96 to 0.42 in 2000-01 and only 2 industries could maintain their ranking in both periods. Under VRS, average efficiency score increased from 0.31 in first period to 0.49 in the second period.

Memon and Tahir (2012) evaluated efficiency of 49 manufacturing firms of Pakistan during the 2008-2010 period using DEA. These companies were categorized as large-sized, medium-sized and small-sized. They used three inputs and two outputs. They found that smaller companies had relatively higher efficiency scores in comparison to large and medium-sized companies. They also found that 2 larger firms, 3 medium-sized firms and 5 smaller firms operated under the most productive scale throughout the period under study.

The aforementioned literature shows that in case of Pakistan, only DEA technique is applied for measuring the efficiency which is not an appropriate approach for measuring the efficiency as its efficiency scores are serially correlated. In this study, DEA double bootstrap technique is employed for measuring the bias-corrected TE scores of LSMI and sources of TE efficiency that is not measured in case of Pakistan. Therefore, this study will contribute to the existing literature about the bias-corrected TE and its sources with respect to the appropriate technique.

III. METHODOLOGY

Measuring the efficiency of producing units was initiated by Farrell (1957). There is much literature with respect to the Farrell's (1957) classic definition of technical efficiency. Basically, there are two common techniques for measuring efficiency: parametric and non-parametric. Aigner et al. (1977) and Meeusen and Broeck (1977) developed the parametric approach (SFA) first. The SFA requires the specification of functional form and estimates the cost frontier. The incorporation of the stochastic error in model specification is the main feature of the SFA. So, this approach allows the testing of hypothesis due to the existence of stochastic error. This approach suffers from two drawbacks: It requires specification of functional form and assumptions regarding distribution of the error term.

The analysis of production efficiency is widely based upon the linear programming models of Charnes et al. (1978) and Fare et al. (1985). The ground is provided for these methods by Farrell (1957). In that literature, those techniques which adopted the convexity assumption are famous with the name of data envelopment analysis (DEA). DEA is a non-parametric approach and it does not require a priori assumption of functional specification relating inputs to outputs and does not demand for the distributional assumption of the error term. DEA creates an efficient frontier for every observation. The maximum output can be gained empirically from a given set of inputs.

In DEA technique, it is assumed that decision making units (DMUs) have full control over the inputs which can be suggested as discretionary variables. But it is not true in reality as Ouellette and Vierstraete (2004) and many others have justified that there are non-discretionary inputs in every sector and therefore, these environmental variables should be used in DEA model. So, many approaches exist in the literature, some of them like Banker and Morey (1986) and Ruggiero (1996) incorporate the environmental variables in DEA model directly and measure the efficiency in a single stage model while others like Ray (1991), Muniz (2002) and recently Simar and Wilson (2007) omit the non-discretionary variables from the DEA model and introduce them in the second stage.

Simar and Wilson (2007) identified severe restrictions with two stages DEA approach which is adopted in existing literature and showed that previous studies which used two-stage DEA approach were defective because of their failure in describing the data generating process (DGP) which put some doubt on the technical efficiency which is explained by DEA efficiency scores. They say that these estimated efficiency scores are serially correlated. Due to these two main reasons the conventional two stages DEA models are statistically invalid. Simar and Wilson (2000) also explained that DEA estimates exaggerate the efficiency scores and underestimate the frontier. In view of these severe problems, Simar and Wilson (2007) adopted the alternative estimation and statistical inference procedure. This procedure enables construction of confidence intervals for efficiency scores on one hand and helps identify determinants of efficiency. In this study, the same approach is employed for analysis.

DATA ENVELOPMENT ANALYSIS AND DOUBLE BOOTSTRAP

In this study, the input-oriented variable returns to scale (VRS) model is applied for getting the TE scores in the first stage because constant returns to scale (CRS) can be employed where industries or firms operate at their optimal scale. The input-oriented DEA efficiency estimator $\hat{\theta}_{ivrs}$ for any data set (x_i, y_i) for each industry can be obtained by solving the following linear programing equation.

$$\hat{\theta}_{vrsi} = \min\left(\theta > 0 \middle| Yi \le \sum_{i=1}^{n} \gamma i Yi; \theta i Xi \ge \sum_{i=1}^{n} \gamma i Xi; \sum_{i=1}^{n} \gamma = 1; \gamma \ge 0, i = 1,...n\right) \qquad \textbf{(1)}$$

In equation (1) x and y are observed inputs and outputs and i=1….,n is the specific industry. The θiXi is the efficient level of inputs, θ is the scalar and γi is the non-negative vector of constants defining the optimal weights of inputs to outputs. The obtained value of $\hat{\theta}_{vrsi}$ is the technical efficiency estimate for the ith industry. In case of input-oriented, inputs should be decreased for getting the higher technical efficiency where $\hat{\theta}_{vrsi}$=1 means that the industry is considered fully efficient while $\hat{\theta}_{vrsi}$>1 means that the industry is inefficient and it needs to reduce the inputs for reducing the inefficiencies.

The bias-corrected efficiencies are estimated in the first stage and are left truncated by 1. The second stage uses a bootstrapped truncated regression estimated by maximum likelihood method to estimate determinants of TE as below:

$$\hat{\theta}vrs_i = b + z_i\beta + \varepsilon_i \quad (2)$$

In Eq. (2), b is the constant term, ε_i is statistical noise, and z_i is a vector of specific variables (these are known as environmental variables) for industry *i* that is expected to be related to the industry's efficiency score.

WHY DOUBLE BOOTSTRAP?

Usually very few results are available for the sampling distribution of interest. It is for this reason that bootstrap techniques are adopted by Simar and Wilson (2000, 2007). The concept behind the bootstrapping is very simple i.e. Simulate the sampling distribution of any specific object by mimicking the data generating process (DGP). The DGP that gives the logic for Simar and Wilson's (2007) double bootstrap is the DEA model represented by eq. (1) and the second step truncated regression described by Eq. (2).

To apply the bootstrap procedure, it is assumed that the original sample data is produced by the DGP and that we can simulate the DGP by using the 'new' or pseudo data set that is derived from the actual data set. Then DEA model is re-estimated by incorporating this new data set. It is possible to derive an empirical distribution of bootstrapped values by doing this process again and again which provides a Monte Carlo approximation of the sampling distribution and also helps out in inference measures. The efficiency of the bootstrapped methodology and the consistency of the statistical inference significantly depend on how well it specifies the true DGP and on the exact re-sampling simulation to copy the DGP.

The Simar and Wilson's (2007) algorithm 2 of bootstrap procedure is employed in this study that provides inference about coefficients and consists of seven steps which are defined in different studies like Barros and Barrio (2011) and Barros and Assaf (2009) briefly.

IV. SELECTION OF DATA

Different inputs and outputs are incorporated in various studies for performance analysis but in this study four inputs and one output are selected for measuring efficiency of large scale manufacturing industries. The description of variables is such that output is contribution to GDP (value of production minus industrial cost minus net non-industrial cost) and inputs are capital (land and building, plant and machinery and other fixed assets), labour (employees, working proprietors, unpaid family workers and home workers), industrial cost (cost of raw materials, fuels and electricity consumed, payments for work done, payments for repairs and maintenance and cost of goods purchased for resale) and non-industrial cost (cost of payments for transport, insurance payments, copy rights and royalties, postage and similar expenses).

V. DATA SOURCES AND REGROUPING OF INDUSTRIES

We selected 65 industries for measuring the efficiency in this study and the analysis of the study covers the period of 1995-96, 2000-01 and 2005-06. The data about inputs and outputs of related large scale manufacturing industries (LSMI)[1] is collected from the census of manufacturing industries (CMI). CMI is basically designed for collecting the data on values of inputs and outputs of LSMI and it reports data in Rs. "000" for inputs and outputs except for employees. The data of inputs and outputs is collected as the value at the end of the period. It was conducted every year before 1990 but after that period it is conducted after five years. The work on CMI 2010-11 is continuing by Pakistan Bureau of Statistics, due to this data availability constraint, the analysis is carried upto the year 2005-06.

For efficiency analysis of industrial sector, 101 industries were selected. But during analysis of the selected industries and their time period, it was found that CMI 1995-96 and 2000-01 followed the Pakistan Standard Industrial Classification (PSIC 1970) which is comparable to International Standard Industrial Classification (ISIC 1968) at four digit level and CMI 2005-06 followed the PSIC 2007 which is developed on the basis of UN International Standard Industrial Classification, ISIC Rev-3.1. It means data of 1995-96 is comparable to the data of 2000-01 because both follow the same classification while data of 2005-06 is not comparable to 1995-96 and 2000-01. So, for making the comparable set of industries, some industries were regrouped on the basis of major activities. Some industries were excluded from the analysis and some were merged in one industry set up for better analysis. After this industrial setting, we were able to regroup the 65 industries which are comparable to each other. The 65 industries were also

[1] According to the definition of CMI, "Large Scale manufacturing covers the establishments registered under factories Act 1934 or qualifying for registration having 10 or more employees". We have used data on LSMI according to this definition.

formed in 22 groups and it was tried to incorporate every major group of industries. Comparable set of industries are presented in table A-1 of appendix.

As it has already been stated in the DEA double bootstrap approach that in the second stage of the analysis, the dependent variable is the bias-corrected efficiencies which are derived from the first step of the procedure. It was regressed against the environmental variables in truncated regression which were assumed to be the sources of technical efficiencies. So, the model at the second stage of regression is showed in the following form.

$$\hat{\hat{\theta}}_{it} = \beta_0 + \beta_1 AW_{it} + \beta_2 SZ_{it} + \beta_3 MS_{it} + \varepsilon_{it} \quad (3)$$

Where, $\ddot{\theta}_{it}$ is the estimated technical efficiency scores based on the assumption of the variable returns to scale. AW represents the average wage which is calculated by the total cost of salaries divided by number of employees, which is counted as the employee's skill and human capital (Kravtsova, 2008). SZ is the industry size which is calculated by taking the logarithm of the employment[2] of the industry, which is considered as a proxy for the economies of scale of the industry in this study. MS is the market size which is calculated by the logarithm of contribution to GDP of a specific group of industries. Finally, ε_{it} represent the statistical noise.

VI. ESTIMATIONS AND INTERPRETATION OF RESULTS

In the first step of the DEA double bootstrap technique, original DEA and bootstrapped VRS efficiencies of 1995-96, 2000-01 and 2005-06 were estimated along with confidence intervals. It was found that original DEA exaggerates the efficiency scores and underestimates the frontier as Simar and Wilson (2000) described the limitations of DEA. It can be noticed that bias-corrected TE scores which are obtained after 2500 simulations, correct the efficiency scores and remove the biasness of exaggeration from the results. The main feature of these estimations is that they also lie within the

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[2] Firstly we used the value of fixed assets as the proxy for the size of the industry but now we used the employment as the proxy for the size of the industry as suggested by reviewer and it is found that this model gives better results than previous model, so it is included in main body of the article and results of previous model presented in table A-5 of Appendix.) For robustness check, we repeated the analysis by using the data of 1995-6 and 2000-01 as per suggested by other reviewer. It has been found that, still there is no efficient industry in case of bias corrected efficiency scores and the results of second stage of this model are presented in table A-4 of Appendix. It could be seen that signs and significance level of this model is same as was the previous model.

confidence intervals while DEA scores do not lie within the interval because it underestimates the frontier and it is assumed to touch the frontier before reaching to the actual one.

As in this study input-oriented DEA Bootstrapped model was used in the first stage, the efficiency score 1 represents the technically fully efficient industry while estimated efficiency score of greater than 1 shows the inefficient or less efficient industry. In case of input-oriented model, fixed output is obtained by utilizing the different set of inputs. So, for minimizing the inefficiencies, use of inputs should be reduced for getting the same level of output. So, it was found that there was not even a single industry fully efficient for the period of 1995-96, 2000-01 and 2005-06 in case of bias-corrected TE. The group-wise mean efficiency analysis is shown in table A-2 of appendix. The efficiency analysis of industrial groups shows broad description of the industrial sector. It can be noticed from this table that almost every industrial group improved its efficiency. It can also be observed from table A-3 of appendix that overall TE of LSMI has increased over the period of time.

After estimating the bias-corrected efficiencies of three cross sections, these bias-corrected efficiencies of three different time periods were pooled in one equation as the truncated regression form showed in Eq. (2) and maximum likelihood method was employed for truncated regression as described in the second step of the Simar and Wilson's double bootstrap procedure in the previous section. Results of determinants of the technical efficiency scores, standard error, t-statistics and bootstrap confidence interval at 95% i.e., lower bound (LB) and upper bound (UB) are presented, respectively in columns 2 to 6 of table 1 in the text. One should remain careful while interpreting the coefficients as it can be seen in the study of Keramidou et al. (2011). Since the efficiency scores are based on the assumption of input-orientation, therefore, signs of coefficients must be reversed during interpretation for clarity in interpretation[3]. It means a positive coefficient shows the negative impact on efficiency scores and vice versa because we

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[33]In this study input-oriented approach is utilized which indicates that firms or industries having a score of 1 are fully efficient while those having efficiency score of greater than 1 are less efficient or inefficient. A coefficient having a positive sign means that the relevant determinant is inversely related to efficiency. While a coefficient having a negative sign means that the relevant determinant leads to enhance the efficiency. In order to have straightforward interpretation we reversed the signs of our regression coefficients during interpretation.

are using input oriented efficiency scores as dependent variable which is larger or equal to one.

TABLE 1

Determinants of VRS TE Scores, Using a Bootstrapped Truncated Regression

Regressor	Bhats	S.E	t-statistic	bootstrapped confidence interval at 95%	
				LB	UB
constant	26.43118	12.74536	2.073789	21.79494	32.00824
Average wage	-15.9285**	5.662649	-2.81291	-19.1232	-13.3802
Size	5.317381**	2.403177	2.212646	3.834783	6.012168
Market size	-2.85637	1.883082	-1.51686	-3.39988	-1.7601

**indicate significance at 5% level.

In the results of second step, where coefficients are bootstrapped 1000 times, average wage, which represents the employee's skill, is a highly significant and possessing a negative sign which shows that it is a favorable source of technical efficiency. It shows that there is more competence, well-educated and post related staffing which enhances the ability of labor to perform and it is participating positively in the efficiency of large scale manufacturing industries. The coefficient of size of the industry (proxy for economies of scale) is significant at 5% level and possesses a positive sign which means it has a negative influence on the efficiency scores. It indicates that it does not help to promote the efficiency of the manufacturing sector and there is no evidence of economies of scale in selected industries and not well utilization of the production capacity. The third and the last coefficient is market size which possesses the negative sign but that is an insignificant variable means it is not participating in affecting the efficiency positively more. These results are found to have the same signs as Keramidou et al. (2011) found in their study.

VI. CONCLUSION

The purpose of this study was to measure the efficiency of the large scale manufacturing industries. Performance analysis is one of the main objectives of the managers of establishments because they want to know that how well are their companies working under the given resources. Performance analysis also helps them to see how well are their past decisions and how they can bring their establishment to the top position. For measuring the efficiency, there are many techniques but in this study, DEA double bootstrap approach was applied because it is more appropriate technique as compared to the existing approaches. DEA double bootstrap consists of two steps. In first step, it measures the bias-corrected efficiency scores while DEA measures the biased efficiencies and it exaggerates the efficiency scores. It can be seen from this study that DEA efficiency scores do not lie in the confidence interval and these scores are beyond the interval due to the bias which exists in DEA scores while bootstrapped efficiency scores lie within the confidence interval and these are bootstrapped by 2500 iterations.

It was found in this study that none of the industries was technically fully efficient while industries showed performance over the period of 1995-96, 2000-01 and 2005-06. It can be seen that the industry which was the most inefficient in 1995-96 was not the highly inefficient in 2005-06 which means that there is learning behavior in industries. In this study, firstly efficiency score of individual and every industry was presented, secondly group-wise efficiency analysis was presented and thirdly overall TE scores were shown.

In the second step of this technique, the bias-corrected efficiency scores are used as the dependent variable with left truncation, the bootstrapped truncated regression model is used because the common standard regression models are inappropriate. In this study, coefficients are bootstrapped with 1000 iterations because further iterations did not improve the results, so 1000 iterations were considered enough in this stage. It was found that there is no evidence of economies of scale in the manufacturing sector and the production capacity is not well utilized. The market size does not have any impact on the efficiencies and the average wage has a negative sign which implies the positive impact on the efficiency scores and it shows that labor is fully able to perform in the favor of technical efficiency due to the well knowledge, more competent and skilled staff.

On the basis of our results, firstly it can be suggested that there is intense need to establish latest technical universities and institutions for the guidance of the labor and to equip them with the modern techniques required by the industry. Secondly industries need to reduce their size as there is evidence of diseconomies of scale.

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APPENDIX

TABLE A-1

: Comparable Set of Industries:

	1995-96 and 2000-01	2005-06
1	**Manufacturing of Textiles**	
1	Cotton spinning	Spinning of textiles
2	Cotton weaving	Cotton fabrics
3	Woolen textiles	Fabrics other than cotton
4	Narrow fabrics	Narrow woven fabrics & embroidery
5	Made-up textile goods	Made-up textile articles, not apparel
6	Knitting mills	Knitted & crocheted fabrics
7	Cordage, rope and twine	Cordage, rope, twine & netting
8	Spooling and thread ball making	Text. yarn & thread of MM staple fibers
2	**Food Manufacturing**	
9	Dairy products &Ice cream & Ice	Dairy Product
10	Canning of fruits & vegetables	Fruit and vegetable juices
11	Canning of fish & sea food	Fish & fish products
12	Vegetable Ghee & Cotton seed and inedible animal oils	Refined oils & fats
13	Rice milling	Rice Husking & Rice milling
14	Wheat & grain milling & Grain milled products and other grain milling	Cereal & vegetable flour milling & Cereal grain products
15	Bread & bakery products	Bread, fresh pastry & cake
16	Biscuits	Rusks, biscuits
17	Refined sugar	Sugar
18	Confectionery, not sweetmeats & Desi" sweetmeats and confectionery	Cocoa, chocolate & sugar confectionery
19	Blending of tea	Processing & blending of tea
20	Feeds for animals & Feeds for fowls	Animal feeds
21	Starch	Starches & starch products
3	**Industrial Chemicals**	
22	Alkalies & Acids, salts & intermediates & Sulphuric acid	Inorganic acids & compound
23	Dyes, colours & pigments	Dyes & pigments
24	Compressed gases, etc.	Industrial gases

25	Fertilizers	Fertilizers & Nitrogen compounds
26	Pesticides, insecticides, etc.	Pesticides & agrochemical products
27	Other industrial chemicals	Chemical elements
4	**Other Non-metallic Mineral Products**	
28	Bricks & tiles	Ornamental & building stone articles
29	Cement	Cement
30	Cement products	Articles of concrete, cement & plaster
5	**Tobacco Manufacturing**	
31	Cigarettes	Tobacco Products
6	**Iron and Steel**	
32	Iron & steel mills	Basic iron & steel
7	**Medicines**	
33	Medicines & basic drugs(allopathic) & Homeopathic and other medicinal preparation	Pharmaceutical preparations
8	**Electrical Machinery and Supplies**	
34	Electrical industrial machinery	DC motors, generators & transformers
35	Radio & television communication	RADIO,TV & COMMUNICATION EQUIPMENT
36	Electrical appliances & Electric fans & Electrical appliances except fans	Electric domestic appliances
37	Insulated wires & cables	Insulated wire and cable
38	Electrical bulbs & tubes	Electric lamps
39	Batteries	Primary cells & batteries & parts
9	**Transport Equipment**	
40	Motor vehicles	Motor vehicles & trailers
41	Motor cycles, auto rickshaws	Motorcycles
42	Cycles & Pedi cabs	Bicycles & invalid carriages
10	**Other Chemical Products**	
43	Perfumes & cosmetics & Polishes & waxes	Perfumes & toilet preparations
44	Soap & detergents	Soaps & detergents
11	**Non-electrical Machinery**	
45	Engines & turbines	Engines & turbines
46	Agricultural machinery	Agricultural & forestry machinery
47	Metal & wood working machinery	Manufacture of machine tools
48	Textile machinery	Spinning, weaving, knitting machinery &other textile machinery

12	**Printing and Publishing**	
49	Books, periodicals, maps, etc.	Printing & publication of books etc.
50	Job printing	Service activities of printing
51	Printed cards & stationery	Other publishing
13	**Petroleum Refining**	
52	Petroleum refining and products of petroleum & coal	Refined petroleum products
14	**Paper and Paper Products**	
53	Pulp, paper & Paperboard	Pulp, paper & paperboard
54	Pulp, paper, board articles & Other paper products	Containers of paper & paperboard
15	**Wearing Apparel**	
55	Ready-made garments	Ready-made garments
16	**Leather and Leather Products**	
56	Tanning and leather finishing	Tanning & dressing of leather
57	Leather products excepts footwear	Luggage, saddlery & harness
17	**Ginning and Baling of Fiber**	
58	Ginning (Cotton and others)	Cotton ginning
18	**Rubber Products**	
59	Tyres, tubes & Retreading tyres & tubes	Rubber tyres & tubes; retreading
60	Vulcanized rubber products	Vulcanised & hard rubber articles
19	**Glass and Glass Products**	
61	Glass and Glass Products	Glass and Glass Products
20	**Non-ferrous Metal Industries**	
62	Aluminium & aluminium alloys	Aluminium, unwrought; alumina
63	Copper & copper alloys	Copper, copper mattes
21	**Surgical Instruments**	
64	Surgical instruments	Medical/surgical/orthopedic equipment
22	**Sports and Athletic Goods**	
65	Sports & athletic goods	Sports goods

TABLE A-2

Mean Efficiencies of the 22 Industrial Groups

t	Group wise mean	1995-96		2000-01		2005-06	
No of group		DEA	dhat.bc	DEA	dhat.bc	DEA	dhat.bc
1	Manufacturing of Textiles	6.21	8.66	3.44	4.23	2.08	2.60
2	Food Manufacturing	6.04	7.98	2.97	3.59	2.67	3.32
3	Industrial Chemicals	3.47	4.67	1.81	2.30	2.03	2.5
4	Other Non-metallic Mineral	2.93	4.10	2.41	3.04	1.72	2.18
5	Tobacco Manufacturing	1	1.67	1	1.44	1	1.43
6	Iron and Steel	2.34	3.49	1	1.44	1	1.40
7	Medicines	6.31	9.54	1	1.45	1	1.25
8	Electrical Machinary	2.98	4.16	2.20	2.63	2.51	3.08
9	Transport Equipment	4.99	6.83	3.11	3.91	2.00	2.44
10	Other Chemical Products	2.40	3.05	1.55	1.77	2.36	2.85
11	Non-electrical Machinery	3.59	4.89	1.38	1.73	1.25	1.71
12	Printing and Publishing	3.70	5.02	1.42	1.74	2.37	2.91
13	Petroleum Refining	1	1.51	1	1.41	1	1.44
14	Paper and Paper Products	4.41	6.01	2.62	3.15	1.98	2.43
15	Wearing Apparel	11.20	16.5	4.08	4.89	1.24	1.55
16	Leather and Leather Products	6.65	8.90	1.87	2.20	3.03	3.64
17	Ginning and Baling of Fibre	4.25	5.92	1.05	1.34	1	1.33
18	Rubber Products	3.80	5.19	1.30	1.51	1.49	1.88
19	Glass and Glass Products	5.22	7.30	2.11	2.65	3.42	4.28
20	Non-ferrous Metal Industries	1.85	2.66	1	1.37	2.17	2.58
21	Surgical Instruments	12.76	15.95	5.57	6.96	3.06	3.76
22	Sports and Athletic Goods	15.16	20.73	1.43	1.59	1.65	1.97

TABLE A-3

Overall T. E. level

Year	DEA	Bias-Corrected efficiencies
1995-96	4.827	6.583
2000-01	2.333	2.871
2005-06	2.132	2.650

For robustness check, by using the data of 1995-6 and 2000-01

TABLE A-4

Determinants of VRS TE Scores, Using a Bootstrapped Truncated Regression

Regressor	Bhats	S.E	t-statistics
constant	9.1716212	8.894823	1.03111898
Average wage	-12.898164**	4.215235	-3.0598917
Size	5.5086915**	1.617621	3.40542863
Market size	-0.6163304	1.14989	-0.5359907

** indicate significance at 5% level

TABLE A-5

Determinants of VRS TE Scores, Using a Bootstrapped Truncated Regression

Regressor	Bhats	S.E	t-statistic	bootstrapped confidence interval at 95%	
				LB	UB
constant	24.47**	11.90	2.06	23.60	33.61
Average wage	-18.68**	6.37	-2.93	-23.53	-16.66
Size	3.31*	1.71	1.93	2.49	3.87
Market size	-1.91	1.67	-1.14	-2.96	-1.49

** and * indicate significance at 5% and 10% levels, respectively