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MEASURING TECHNICAL, SCALE, COST AND ALLOCATIVE EFFICIENCY IN THE MANUFACTURE OF BASIC METALS IN INDIA USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

There are two approaches for estimation of efficiency, viz., the Stochastic Frontier Approach (SFA) and Data Envelopment Approach (DEA). While the SFA (econometric approach) estimates the efficiency of the firms by estimating the production function, the DEA technique involves the use of mathematical programming to estimate the efficiency of the firms / industry. For the period 2002-3 to 2011-12, the calculations on the efficiency of Decision Making Units (DMUs) in the manufacture of basic metals in India have been done. The paper demonstrates that the technical, scale, cost and allocative efficient DMUs were more under Variable Returns to Scale (VRS) production technology in comparison with Constant Returns to Scale (CRS) production technology.

Keywords: Allocative efficiency, BCC MODEL , CCR Model , cost efficiency, Decision Making Units(DMU), scale efficiency, Variable Returns to Scale (VRS).

INTRODUCTION

India's manufacturing sector is vital for its economic progress. The contribution of manufacturing to overall GDP is meager 17.2 per cent (2014-15). The government has realized the importance of this sector to the country's industrial development, and has taken a number of proactive steps to further enhance the industry. Manufacturing Industry in India has gone through various phases of development over the period of time.

Since independence in 1947, the Indian manufacturing sector has traveled from the initial phase of building the industrial foundation in 1950's and early 1960's, to the license–permit Raj during the period of 1965–1980, to a phase of liberalization of 1990's, emerging into the

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current phase of global competitiveness. It has grown at a robust rate over the past ten years and has been one of the best performing manufacturing economy. Studies have estimated that every job created in manufacturing has a multiplier effect, creating 2–3 jobs in the services sector. In a country like India, where employment generation is one of the key policy issues, this makes manufacturing a critical sector to achieve inclusiveness in growth.

The metal sector is a key part of manufacturing. It is highly sensitive to changes in the business cycle. It is considered a capital- (basic metals), labour- (fabricated metal products) and energy-intensive industry, producing a wide range of products e.g. basic metals, tanks, steam generators, cutlery, tools, light metal packaging, wires etc. The metal industry is an important component of the world economy when measured by its share of GDP worldwide. In sub-branches such as metal production, non-electrical machinery, electrical machinery and transport equipment, it employs some 70 million workers worldwide, who account for nearly half of the goods produced in the manufacturing sector and more than half of all merchandise exported worldwide (in terms of value).Consequently, the metal industry is both a driving force of the world economy and is influenced to a large extent by the overall world economic climate.

METHODOLOGY

1. Data Base of the Study

The basic data source of the study on fixed capital, wages, net value added and number of workers was Annual Survey of Industries (ASI) published by the Central Statistical Organisation (CSO), Government of India. All the referred variables were normalised by applying Gross State Domestic Product (GSDP) deflator. The GSDP at current and constant prices were obtained by referring to the Economic Survey, published by the Government of India, Economic Division of the Ministry of Finance, New Delhi .The reference period chosen for the study covers post- liberalization period between 2000-01 and 2011-12.The availability of data is confined only up to this period.

2. Tools of Analysis

DEA Model

There are basically two approaches for estimation of efficiency, viz., the Stochastic Frontier Approach (SFA) and Data Envelopment Approach (DEA). While the Stochastic Frontier Approach (econometric approach) estimates the efficiency of the firms by estimating the production function, the DEA technique involves the use of mathematical programming to estimate the efficiency of the firms / industry. DEA is a non-parametric, deterministic methodology for determining relatively efficient production frontier, based on the empirical data on chosen inputs and outputs of a number of entities called Decision Making Units (DMUs). From the set of available data, DEA identify reference points (relatively efficient DMUs) that define efficient frontier (as the best practice production technology) and evaluate the inefficiency of other interior points (relatively inefficient DMUs) that are below the frontier (Saon Ray, 2004).

The DEA provides a measure of efficiency that allows intra-firm comparison, as the efficiency measure is a pure number. The main advantage of DEA is that unlike SFA, it does not require a priority assumption about the analytical form of the production function. Instead, it constructs the best practice production solely on the basis of observed data and therefore the possibility of mis-specification of the production technology is minimized. In the case of SFA, the parameter estimates are sensitive to the choice of the probability distribution specified for the disturbance term.

There are two approaches to estimating the efficiency of the firm in the DEA approach viz., the output-oriented efficiency and the input-oriented efficiency. In the output-oriented approach, efficiency is determined by maximum output that can be produced from an input bundle. In the input-based measure, the technical efficiency of the firm is evaluated by the extent to which all inputs could be proportionally reduced without a reduction in the output. Among number of DEA models, the two most frequently used ones (input-oriented) are, CCR model (after Charnes, Cooper, Rhodes, 1978) and BCC model (after Banker, Charnes and Cooper, 1984), both of which are used in the study. The DEA model is used to estimate the technical, scale, cost and allocative efficiency of the industries under study.

I. TECHNICAL EFFICIENCY

(i) CCR Model (based on constant returns to scale)

Charnes, Cooper and Rhodes(1978) introduced a measure of efficiency for each DMU that is obtained as a maximum of ratio of weighted outputs to weighted inputs. The weights for the ratio are determined by a restriction that the similar ratios for every DMU have to be less than or equal to unity, thus reducing multiple inputs and outputs to single "virtual" output without requiring pre-assigned weights.

The efficiency measure is then a function of weights of the "virtual" input-output combination. Formally, the efficiency measure for the DMU can be calculated by solving the following mathematical programming problem:

$$\max h_0(u,v) = \frac{\sum_{r=1}^{S} u_r Y_{ro}}{\sum_{i=1}^{S} v_i x_{io}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$\text{Subject to} \quad \frac{\sum_{r=1}^{S} u_r Y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1,2\ldots\ldots, j_o, \ldots\ldots, n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$u_r \leq 0, r = 1,2,\ldots., s \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$v_i \geq 0, j = 1,2,\ldots., m \quad \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

where the observed amount of input of the i^{th} type of the DMU > 0,

i = 1,2,......n, j = 1,2,.....n) and = the observed amount of output of the r^{th} type for the j^{th} DMU (Y_{rj} > 0, r = 1,2,.....s, j = 1,2,...n).

The variables U_r , and V_i are the weights to be determined by the above programming problem. However, this problem has infinite number of solutions since if (u*, v*) is optimal, then for each positive scalar, α (αu*, αv*) is also optimal. Following the Charnes - Cooper transformation (1962), one can select a representative solution (u,v) for which to obtain a linear programming problem that is equivalent to the linear fractional programming problem (1) - (4). Thus, denominator in the above efficiency measure h_0 is set to equal one and the transformed linear problem for DMU can be written.

$$\sum_{i=1}^{m} v_i x_{i\,o} = 1 \qquad .... (5)$$

$$\max z_0 = \sum_{r=1}^{S} u_r \; Y_{r\,o} \qquad .... (6)$$

Subject to $$\sum_{r=1}^{S} u_r Y_{r\;j} - \sum_{r=1}^{m} v_i x_{i\,j} \le 0,\; j = 1,2,\ldots,n ....(7)$$

$$\sum_{r=1}^{m} v_i \; x_{i\,o} = 1 \qquad .... (8)$$

$u_r \ge$ 0, r = 1,2,...., s .... (9)

0, i = 1,2,...., m .... (10)

For the above linear programming problem, the dual can be written (for the given DMU) as:

$\min z_0 = \Theta_o$ .... (11)

Subject to

$$\sum_{j=1}^{n} \lambda_r \; Y_{r\;j} \ge y_{ro} \quad r = 1,2,...,s \qquad .... (12)$$

$$\Theta o x_{io} - \sum_{j=1}^{n} \lambda_j x_j \ge 0, i = 1,2,\ldots,m \qquad .... (13)$$

$\lambda_j \ge$ 0, j = 1,2,...,n .... (14)

Both of the above linear problems yield the optimal solution Θ^*, which is the efficiency score (so-called Technical efficiency or CCR efficiency) for the particular DMU and repeating them for each DMU_j , j = 1,2,....n, efficiency scores for all of them are obtained. The value of Θ is always less than or equal to unity (since when tested, each particular DMU is constrained by its own virtual input-output combination too). DMUs for which $\Theta^* < 1$ are relatively inefficient and those for which $\Theta^* = 1$ are relatively efficient, having their virtual input-output combination points lying on the frontier. The frontier itself consists of linear facets spanned by efficient units of the data and the resulting frontier production function (obtained with the implicit constant returns to scale assumption) has no unknown parameters.

(ii) BCC Model (based on Constant Returns to Scale)

Since there are no constraints for the weights λ_j , other than the positivity conditions in the problem (11) - (14), it implies constant returns to scale. For allowing variable returns to scale, it is necessary to add the convexity condition for the weights, λ_j, i.e. to include in the model (11) - (14) the constraint:

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad \text{.................... (15)}$$

The resulting DEA model that exhibits variable returns to scale is called BCC model, after Banker, Charnes and Cooper (1984). The input-oriented BCC model for the DMU_0 can be written formally as:

$$\min z_0 = \Theta o \qquad \text{..................... (16)}$$

Subject to

$$\sum_{j=1}^{n} \lambda_r \, Y_{rj} \geq Y_{ro} \quad r = 1,2,...,s \qquad \text{.................... (17)}$$

$$\Theta_0 x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, i = 1,2,...,m \qquad \text{..................... (18)}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad \text{..................... (19)}$$

$$\lambda_j \geq 0, \quad j = 1,2,...,n \qquad \text{..................... (20)}$$

Running the above model for each DMU, the BCC efficiency scores are obtained (with similar interpretation of its values as in the CCR model). These scores are also called "pure technical efficiency scores", since they are obtained from the model that allows variable returns to scale and hence eliminate the "scale part" of the efficiency from the analysis. Generally, for each DMU, the CCR efficiency score will not exceed the BCC efficiency score, what is intuitively clear since in the BCC model each DMU is analyzed "locally" (i.e. compared to the subset of DMUs that operate in the same region of returns to scale) rather than "globally".

II. SCALE EFFICIENCY

Following the scale properties of the above two models, (Cooper et al., 2000) the scale efficiency is defined as follows: *For a particular DMU, the scale efficiency is defined as a ratio of its overall technical efficiency score (measured by the CCR model) and pure technical efficiency score (measured by the BCC model).*

III. COST EFFICIENCY

The standard measure of cost efficiency is obtained via two stage process:

(i) Estimate the minimum price-adjusted resource usage given technological constraints; and (ii) Compare this minimum to actual, observed costs. Cost efficiency can be measured if input prices are available in addition to output and input data. Let x =(x_1, ...x_k) εR_+^k denotes a vector of inputs and y = (y_1, ...y_m) εR_+^m denote vector of outputs. Formally, the cost efficiency model can be specified as :

$$\mathrm{Min}_{z,x} \sum_{j=1}^{m} w_{j\,o}\, x_j \qquad \text{.....................} (21)$$

$$\begin{aligned} \text{s.t.} \quad & z.Y \leq y_0 \\ & z.x \leq x_0 \\ & zi \geq 0 \\ & \sum_{i=1}^{n} z_i = 1 \end{aligned}$$

where Y is an *n* x *m* matrix of observed outputs for n industries and x is an *n* x *k* matrix of inputs for each industry. z is a *l* x *n* vector of intensity variables and w = (w_1,...w_k) εR_+^k denoted input prices. The constraints of the model (21) define the input requirement set given by:

$$L(y) = (x.\ z.\ y \geq y_0,\ z\,x \leq x,\ z_i \geq 0,\ \sum_{i=1}^{n} z_i = 1) \qquad \text{.....................} (22)$$

The input requirement set specifies a convex technology with Variable Returns to Scale (VRS), which is imposed by the constraint $\sum_{i=1}^{n} z_i = 1$. Leaving the constraint out of the model changes the technology to Constant Returns to Scale (CRS).

IV. ALLOCATIVE EFFICIENCY

Allocative efficiency is defined as a ratio of cost efficiency score to technical efficiency score. Both under CRS production technology and VRS production technology, this efficiency score was estimated for the present study.

RESULTS AND DISCUSSION

A. Technical Efficiency

The results regarding technical efficiency scores of the selected intermediary goods industries are presented in Table-1.

Table 1: Technical Efficiency (TE) Estimates

DMUs	CRS*	VRS**
2002-03	0.324	1.000
2003-04	0.470	1.000
2004-05	0.595	1.000
2005-06	0.959	1.000
2006-07	0.669	0.865
2007-08	0.853	0.872
2008-09	1.000	1.000
2009-10	0.736	0.785
2010-11	0.778	0.814
2011- 12	0.780	0.791
Average Technical Efficiency	0.716	0.913
Average Technical Inefficiency	0.397	0.095
No of Technical inefficient DMUs	1	5

CRS*- Constant Returns to scale; VRS*- Variable Returns to scale;

(*Source*: Calculations based on ASI data)

Under Constant Returns to Scale (CRS) production technology, technical efficiency between 2002-03 and 2011- 12 was 0.716. This implied that the industry would have needed only 71.6 percent of the inputs currently being used. In terms of average inefficiency, it would have needed 28.4 percent more inputs to produce the same output, which meant waste of resources to the extent mentioned above.

Under VRS production technology, the number of efficient DMUs exceeded the number of efficient DMUs under CRS production technology. Under VRS production technology, higher average efficiency was always recorded. It may be due to the reason that DMUs that were efficient under Constant Returns of Scale (CRS) were accompanied by the new efficient DMUs that might operate under increasing or decreasing return to scale. Higher degree of average technology inefficiency particularly under constant return to scale production technology can be attributed to the fact that the industry may not be using the most efficient technology available to transform the input into outputs due to differences in products, the industry was likely to have different best practice frontiers; relatively small regional spheres of operation of the industry may have resulted in inefficiencies; and structured problems regarding staff efficiency and operating efficiency may have prevented the firm from improving its efficiency level. It can be concluded that though the efficiency of the firms varied considerably on account of the various reasons mentioned, the firm was estimated to be on the frontiers at least once. In other words, both under CRS and VRS technology, the number of efficiency scores or levels during the entire period, was indicative of the fact that the efficiency of firm was not strongly influenced by the size of production.

B. Scale Efficiency

The scale efficiency scores is presented in Table-2

Table 2 :Scale Efficiency(SE) Estimates

DMU	**CRS*(TE)**	**VRS(TE)**	**Scale Efficiency (CRS(TE) / RS(TE)**	**RTS****
2002-03	0.324	1.000	0.324	IRS***
2003-04	0.470	1.000	0.470	IRS
2004-05	0.595	1.000	0.595	IRS
2005-06	0.959	1.000	0.959	IRS
2006-07	0.669	0.865	0.774	IRS
2007-08	0.853	0.872	0.978	IRS
2008-09	1.000	1.000	1.000	CRS
2009-10	0.736	0.785	0.938	IRS
2010-11	0.778	0.814	0.955	IRS
2011- 12	0.780	0.791	0.986	IRS
Average Scale Efficiency	0.716	0.913	0.798	
Average Scale Inefficiency	0.716	0.913	0.253	
No of Scale Inefficient DMUs	1	5	1	

CRS* – Constant Returns to Scale; RTS** - Returns to Scale; IRS*** - Increasing Returns to Scale; Average scale inefficiency = 1-

(*Source*: Calculations based on ASI data)

DEA results applied to know the scale efficiency of industries for the entire period revealed that the industries were not operating at an optimum scale. The average scale efficiency was 84.6 percent. In terms of average inefficiency, it could increase additional production to the extent of 15.4 percent, by taking advantage of their scale characteristics. DEA allows to assess whether a firm lies in the range of increasing, constant and decreasing returns to scale. In other words, it revealed the scale characteristics of DMUs. If market contains firms scale, market efficiency can be increased if more DMUs attain constant returns to scale, because fewer resources are wasted. The measurement of economies of scale, therefore, helps assess at the same time whether higher market concentration should be encouraged to improve efficiency. A DMU may be scale inefficient, if it experiences decreasing returns to scale or if it has not taken full advantages of increasing returns to scale. Indeed most of the inefficient DMUs presented increasing returns to scale characteristics which indicated that industries can increase the scale to effectively improve that efficiency.

C. Cost efficiency

Table 3 gives details regarding cost efficiency scores of selected industries for the reference period under study.

Table 3:Cost Efficiency (CE) Estimates

DMU	CRS*	VRS**
2002-03	0.269	1.000
2003-04	0.405	0.999
2004-05	0.548	0.975
2005-06	0.882	1.000
2006-07	0.643	0.825
2007-08	0.798	0.860
2008-09	1.000	1.000
2009-10	0.703	0.737
2010-11	0.650	0.674
2011- 12	0.668	0.676
Average Cost Efficiency	0.657	0.875
Average Cost Inefficiency	0.522	0.142
No of Cost efficient DMUs	1	3

CRS*- Constant Returns to scale; VRS**- Variable Returns to scale;

Average cost inefficiency = 1-

(*Source*: calculations are based on ASI data)

Under Constant Returns to Scale (CRS) technology, the industry was efficient to the extent of 65.7 percent. Under Variable Returns to Scale (VRS) production technology the industry was more efficient to the extent of 87.5 percent. The cost efficient DMUs, it was found to be more under VRS production technology. The average cost inefficiency was more under CRS production technology than under VRS production technology.

D. Allocative efficiency

Allocative efficiency scores of the industries under the reference period is presented in Table.4.

Table 4: Allocative Efficiency (AE) Estimates

DMU	CRS	VRS
2002-03	0.831	1.000
2003-04	0.861	0.999
2004-05	0.921	0.975
2005-06	0.920	1.000
2006-07	0.961	0.954
2007-08	0.936	0.986
2008-09	1.000	1.000
2009-10	0.956	0.939
2010-11	0.836	0.828
2011- 12	0.857	0.855
Average Allocative Efficiency	0.908	0.875
Average Allocative Inefficiency	0.101	0.143
No of Allocative efficient DMUs Inefficient DMUs	1	3
CRS*- Constant Returns to scale; VRS**- Variable Returns to scale Average Allocative inefficiency = 1- (*Source*: Calculations are based on ASI data)		

Estimates revealed that over the study period, the industries under CRS production technology had on an average allocative efficiency level of 91 percent implying that the industries were 9 percent inefficient, respectively. In the case of VRS production technology, an average allocative efficiency of 88 percent has been measured, implying that the industries were on an average 12 percent inefficient. More efficient DMUs were observed in VRS production technology in comparison with the CRS production technology.

CONCLUSION

For the entire period, technical, scale, cost and allocative efficient DMUs were more under Variable Returns to Scale (VRS) production technology in comparison with Constant Returns to Scale (CRS) production technology. It is very clear that inefficiency could be due to the existence of either increasing or decreasing returns to scale.

REFERENCES

1. Banker.R.D Charnes.A & Cooper.W.W (1984). Some Models For Estimating Technical And Scale Inefficiencies In Data Envelopment Analysis, *Management Science*, Volume. **30**, pp.1078-2092.
2. Charnes.A, Cooper, W.W & Rhodes.E (1978). Measuring The Efficiency Of Decision Making Units, *European Journal Of Operation Research*,Volume.**2**, pp.429-444. Available online at http://www.utdallas.edu/~ryoung/phdseminar/CCR1978.pdf