Enhanced DEA to Compare Performance of Automobile Models based on Two-Dimensional Warranty Data

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Abstract – *In case of an automobile, warranty is characterized by its age and usage. A manufacturing company, most of the cases, only knows the age and usage of an automobile if it fails within two-dimensional warranty coverage. The manufacturing company may also know the number of automobile survived beyond the warranty coverage and overall profit. The present study is designed to measure the technical efficiency (TE) of different automobile models of a company with the same warranty coverage based on two-dimensional warranty data. An enhanced data envelopment analysis (E-DEA) based on constant return to scale (CRS) technique is applied in this paper to compare the efficiency and also to rank models accordingly. In this study the number of automobiles sold in a given time span, cost of raw materials, electricity consumption and average wage of workers are selected as input variable and the percentage of automobiles survived beyond warranty coverage, average age of the failed cars within warranty coverage, average usage of the failed cars within warranty coverage, and profit per unit of production cost are taken as output variable. The five models under a non-renewal free replacement policy of a renowned company are compared using enhanced DEA. It has been depicted from a bootstrapped Tobit regression model that mainly the size (small, medium and large) of the automobile, number of workers involved to produce models, the average period between production and sale of an automobile model, manager's experience, and average repair/ replacement time are significant determinants of efficiency score.*

Key Words: DEA, CRS, Efficiency, Warranty, Determinants, Bootstrapped Tobit regression

1. INTRODUCTION

Automobile industry plays an important role in the world economy. As a result, the effect of globalization is mostly influenced in this sector. There is a fierce competition among the automobile companies globally. Different automobile companies launch different models with a variety of features to survive in the market. Few models run well in the market and some models do not. Thus, for a manufacturing company this is required to compare the field performance of the models to check the efficacy of the models. Generally, a manufacturer knows the lifetime of an item if it fails within the warranty coverage. Warranty is basically an assurance of a manufacturer to a customer to replace the failed parts within a stipulated coverage without taking any remuneration (free repair/ replacement policy) or taking a very small part of the repair/ replacement cost (pro-rata policy). In case of automobile warranty is characterized by two-dimensions, i.e., age and usage. For example the repair/replacement of any item for a car is carried out free of cost up to 3 years or 36000 miles, whichever occurs first. Thus, it is expected that if a car fails within minimum of age and usage limits, then a customer reports the lifetime of the car in terms of age and usage to the manufacturing company to enhances benefits of warranty policy and thus the manufacturer will able to known the field performance of it. On the basis of two-dimensional warranty data lot of researchers evaluate the performance of cars ([1]-[6] etc.). Most of them evaluated the performance of a car with the yard sticks like reliability, hazard rate, expected life etc. Gupta et al. [4] compared the superiority of the performance of the automobiles in two different places of the same automobile company using conditional reliability, hazard gradient and expected number of joint and conditional failures. In this context they have developed layered non homogeneous Poisson process. Warranty cost may also be looked upon as an indicator of performance of an automobile. There are some papers that deal with cost of the repair/replacement to estimate cost within warranty ((7)-[9] etc.), But to compare different models of manufacturing items it is justified to consider cost, age, usage and number of failure together. In this present paper data envelopment analysis (DEA) is applied to test superiority of the models considering different inputs and outputs. Frontier efficiency technique can be utilized to determine the efficiency score. Two frontier techniques can be adopted for evaluating efficiency, namely, data envelopment analysis (DEA) and stochastic frontier analysis (SFA). However, this paper only concentrates on DEA because the analysis can be done without considering a particular functional form/shape of the frontier. Charnes et al. [10] extended Farrell's [11] idea by making a bridge between the estimation of technical efficiency and production frontiers. This model is known as Charnes-Coopper-Rhodes model or simply CCR model. DEA is a relatively new data oriented approach for measuring the technical efficiency of a group of peer entities called decision making units (DMUs). It is also a non-parametric technique and it solves linear programming problems (LPPs). DEA can also be performed without predetermining the weights of inputs and outputs. Additionally, for estimation of efficiency score there is no need of the setting of a production function. DEA is very useful for comparing the efficiency of productive units in various economic sectors, including the automotive industry.

A review of published literature shows that the application of DEA in automobile industry is limited. A small section of studies used the DEA model to compare automobile efficiency. Kumar et al. [12] investigated the technical efficiency of automobile manufacturing firms in India from 2011-12 to 2015-16. Smriti and Khan [13] applied DEA to measure efficiency score of 1007 automobile firms. The significant determinants behind the inefficiency found in this analysis includes mainly the firm size, manager's experience in respective sectors, annual losses due to power outage and number of workers. Jiang et al. [14] performed efficiency estimation of 77 automobile firms during the period 2012 to 2016 basd on DEA and Malmquist models. They have considered fixed assets, intangible assets, the operating expenses and the number of employee as inputs and the income as output. DEA and Malmquist productivity analysis have been conducted by Martiz and Shieh [15] to measure the total efficiency, pure technical efficiency, and scale efficiency of nine automobile businesses in Taiwan. Partovi and Kim [16] adopted DEA for estimating efficiency of vehicle of five categories (diesel, gas, hybrid gas/electric, fully electric, and hydroden vehicles) to identify the most efficient vehicle. The vehicles were compared based on the type of fuel the vehicle consumed. Svoboda and Lagasse [17] adopted DEA to determine the relative efficiency of twelve consumer electric vehicles on the market. Papahristodoulou [18] evaluated car efficiency using DEA. Saranga [19] applied DEA for measuring technical, input mix and scale efficiency of Indian auto component industries.

Although having several advantages, simple DEA exhibits some limitations. It actually evaluates whether an entity or a company or a DMU is efficient or not. But it fails to assign ranks among the efficient units as all the efficient units have the same efficiency score of 1. Therefore it is difficult to compare DMUs if there is large number of efficient units. Additionally, efficiency scores are very much sensitive to the number of inputs, outputs and the size of the sample. Thereby, with large sets of inputs and outputs, the lack of ranking makes poor discrimination among the efficient units. These limitations imposed a serious problem in using DEA to compare different units or entities. Improving the discriminatory power has raised a serious challenge that has increased a significant research interest. Various methods have been invented to deal with the ranking of DMUs. But these methods fail to provide a complete solution of the ranking problem. To overcome the problems of standard DEA, Das [20] suggested the idea of enhanced DEA technique that can be able to solve the ranking problem in a better way. Latter, Oral [21] has studied the enhanced DEA in details. Gala'n and Martı'n et al. [22] also used enhanced DEA to check sustainability in the electricity sector. Their approach incorporated the concept of efficiency with the standard DEA. Here the standard DEA is applied several times with different combinations of inputs using standard DEA and then the average of all of the efficiency scores obtained for all the orders produces the ultimate efficiency score. It enables to assign distinct rank to the different units most of the cases. Ordinary DEA does not evaluate cross efficiency [23]. Enhanced DEA incorporates both self-efficiency and cross-efficiency scores. Additionally, it provides clear quantitative target for the inefficient units to become efficient. The literature covers the issue of application of DEA in automobile industry fails to rank the DMU's properly if there are several efficient units. Also, there is no research paper, best of my knowledge, which discusses frontier efficiency measure based on warranty data. In this paper I want to reduce this research gap. The enhanced DEA method will enable to rank the DMU's. Also the variables that are related to production and sell of a product are considered as input and the failure related information from the warranty data is taken as output.

After the estimation of the efficiency scores, determination of the determinants of the efficiency is another important task. One can use ordinary least square (OLS) regression for this purpose. Saranga [19] used OLS to find the determinants of the operational efficiency scores of Indian auto component industries. Smriti and Khan [13] found that the significant determinants behind the inefficiency are the firm size, managers' experience in respective sectors, annual losses due to power outage, number of workers. However, since the value of efficiency lies between 0 and 1, Tobit regression may suitable one instead of OLS. Different factors like size (small, medium and large) of the automobile, number of workers involved to produce a particular automobile model, the average period between production and sale of a model, manager's experience, average repair/ replacement duration for a car, average number of seating capacity etc. are taken as explanatory variable in case of Tobit regression in this present paper.

2. DEA AND ENHANCED DEA

DEA was first developed by Charnes et al. [10] , who establishes a linear combination of outputs and inputs to measure the efficiency for observes by integrating the outputs/inputs ration efficiency measure (CCR model).

Here CCR model is under the assumption of constant return to scale (CRS) production technology. The reason of considering CRS is that all the car models are selected from the same company with the same warranty coverage and hence it can be assumed that the samples are more or less homogeneous.

Let x_{ij} (>0) be the observed magnitude of *i*- type input for the j-th entity, *i=1,2,…, I, j=1,2,…,J* and y_{kj} (>0) be the observed magnitude of *k*-type output for the j-th entity, *k=1,2,…,K, j=1,2,…,J.* Then, the Charnes-Cooper-Rhodes (CCR) model can be formulated as:

$$Maximize \quad \theta_j = \sum_{k=1}^{K} u_k\, y_{kj} / \sum_{i=1}^{I} v_i\, x_{ij}$$

Subject to

$$\sum_{k=1}^{K} u_k y_{kj} - \sum_{i=1}^{I} v_i x_{ij} \le 0 \text{ for all } j=1,2,\dots,J; \quad (1)$$

$u_k, v_i \ge 0$ for all *k=1,2,..,K, i=1,2,…,I.*

Here θ_j is the technical efficiency (TE) for the selected entity *j* and u_k and v_i are the weights to be determined for output *k* and input *i* respectively. If $\theta_j=1$, then the *jth* entity is said to be achived efficiency. But the *jth* entity does not achive efficiency if $\theta_j \le 1$. The above nonlinear model can be converted into a linear one by representing it in the following way:

$$Maximize \quad \theta_j = \sum_{k=1}^{K} u_k\, y_{kj}$$

Subject to

$$\sum_{i=1}^{I} v_i x_{ij} = 1$$

$$\sum_{k=1}^{K} u_k y_{kj} - \sum_{i=1}^{I} v_i x_{ij} \le 0 \text{ for all } j=1,2,\dots,J; \quad (2)$$

$u_k, v_i \ge 0$ 0 for all *k*= 1 to *K*, *i*= 1 to *I*.

In practice, it is often solved dual task of equation (2), which is

$$Z = Minimum\, \theta_0 - \in (\sum_{k=1}^{K} S_k^+ + \sum_{j=1}^{I} S_i^-)$$

Subject to

$$\sum_{j=1}^{J} \lambda_j y_{kj} - S_k^+ = y_{k0}$$

$$\sum_{j=1}^{J} \lambda_j x_{ij} + S_i^- = \theta_0 x_{ik0}$$

λ_j, S_i^-, $S_k^+ \ge$ 0 for all *i=1,2,…, I; j=1,2,…,J* and *k=1,2,…, K* (3)

ϵ = a small positive value

θ_0 = unconstrained efficiency

$$y_{k0} = \sum_{j=1}^{J} y_{kj}, \quad x_{i0} = \sum_{j=1}^{J} x_{ij}$$

S_k^+ and S_i^- are the slack variables

λ_j=weights of *jth* efficient *DMU*

The most widely used DEA model is CRS with input orientation among different existing models. The CRS models are developed on under the assumption of constant returns to scale.

But as told earlier the basic DEA model allows to identify whether a unit is efficient or not. Thus, sometimes it creates problem to rank DMUs. So this is required to introduce the concept of 'order of efficiency'. The order of efficiency of a DMU under input model determines least number of all possible combinations of inputs that make the particular DMU efficient. Here higher orders imply lower degrees of efficiency. An optimal solution in case of enhanced DEA is said to be efficient of order q if it is not dominated by any other optimal solution in any of the possible q elements subject of objectives. A DMU is identified an efficient of order q if and only if it is found efficient in any of the possible q elements subsets of input. If a DMU is efficient of order q, it is also efficient of order q_1>q. To compute the efficiency of order q, it is required to estimate DEA for every possible combination of inputs/outputs. Thus, in case of enhanced DEA the standard DEA should be repeated for all possible combinations of inputs/outputs and then aggregated into an overall efficiency metric. The efficiency for the *jth* DMU using enhanced DEA can be determined by

$$\theta_j = \sum_{q \in Q} \sum_{s \in S_q} \theta_{jsq} / \binom{N}{q} \quad (4)$$

Where,

N= Cardinal of the set of inputs

Sq=Set of combinations of order q of the inputs

Q=Set of allowable orders

θ_{jsq}=Efficiency score of DMU_j in each combination of inputs s_q belongs to S_q

Here also θ_j lies in [0,1]. If θ_j =1 then jth unit is said to be efficient. The efficiency allows ranking of all DMUs in terms of performance.

Now, for each inefficient unit, the corresponding targets that is input should achieve to make the unit efficient cam be determined. Suppose ω denotes the reference set of efficient DMUs *j* for an inefficient DMU *j'*. Then the target value for input i that DMU j' should attain is computed as follows:

$$\text{Target input}_{j'i} = \sum_{j \in \varpi} \lambda_j x_{ij} = \theta_{j'} x_{ij'} - s_i^- \qquad (5)$$

Where $\theta_{j'}$ is the efficiency score of the inefficient unit j' and s_i^- is a slack variable denoting the extra amount by which the input i should be decreased to be efficient. In this way one can also identify the inputs for which DMU is inefficient.

3. BOOTSTRAPPED TOBIT REGRESSION

To identify the determinants of efficiency score of automobile models it is required to regress some relevant explanatory variables with efficiency score obtained by applying enhanced DEA. Ordinary least square (OLS) is a usual way for regression analysis. But as efficiency score are bounded by 0 and 1, it is appropriate to use a limited dependent variable approach. The Tobit regression model is an alternative of OLS regression. Tobin introduced a Tobit model to study the relationship between a non-negative dependent variable and independent variable [24]. Tobit model is also termed as a truncated or censored regression model to provide technical efficiency scores of DMUs under a restricted range of values of the dependent variable. The two-limit Tobit model is given as:

$$E_j^* = \beta_0 + \beta_1 u_{ji} + \beta_2 u_{j2} + \ldots + \beta_l u_{jl} + \varepsilon_j \quad (6)$$

$$E_j = E_j^* \; if \; 0 \le E_j^* \le 1; = 0\,(1) if \; E_j^* \le (\ge)\, 0\,(1) \quad (7)$$

Here E_j is the efficiency score corresponding to the *jth* DMU and $u_{j1}, u_{j2},\ldots,u_{jl}$ are the independent variables represents automobile specific characteristics required for the study. $\beta_0, \beta_1, \beta_2, \ldots, \beta_l$ are the coefficients of Tobit regression. ε_j is a random error component and it follows a normal distribution with mean 0. The Tobit model employes the Newton Raphson model based on maximum likelihood function. As in case of DEA, dependent variable represents relative efficiency scores which lie between 0 and 1, it can be treated as censored from left as well as from right. Thereby, Tobit model can be applied in second stage to identify the determinants. When the variables of Tobit regression model are correlated with the efficiency scores, then it creates the inconsistency problem of estimators. A bootstrap method is used to overcome this drawback [25]. Separability condition is checked empirically [26].

4. DATA ANALYSIS

This study incorporates five different car models of a renowned automobile company as decision making units (DMUs). The name and features of the models are not disclosed in detail for confidential reasons and only the salient features required for this analysis are revealed. The car models are renamed as A, B, C, D and E. Among these models A and E are relatively larger, B and C have medium or normal size and D is relatively smaller. Also the two models B and D are comparatively new in the market. The two-dimensional coverage of the models is 3 years and 36 Kilo-miles in the direction of age and usage respectively. These models are sold during 2015 to 2018. The cars are protected under a non-renewing free replacement warranty policy. The age, usage number of failure within warranty, corrective measure cost have been determined from the warranty data base. 2372, 4715, 3288, 2764 and 1227 are the number of cars for respective models A, B, C, D and E that sold in the time span 2015-18. Among these sold cars the number of failures within the warranty coverage is 851,1137, 1257, 1115 and 794 for A, B, C, D and E respectively. Other relevant information has also been gathered. This paper dealt with both DEA and enhanced DEA (E-DEA) to determine the efficacy of the car models. The inputs used for this study are the number of cars sold during the time span, cost of raw materials, cost of electricity and average wage of the worker associated with each model. Percentage of automobile survived beyond the warranty, average age of the failed cars, average mileage of the failed cars, and profit per unit of production cost are taken as outputs. To make unit free the variables or the reciprocal of the variables are normalized accordingly whichever is required as our basic aim is to minimize input per unit of better output. In case of input approach the efficiency score represents the extent to which all the inputs should be proportionally reduced to reach frontier. The efficiency scores applying DEA and enhanced DEA are estimated for five DMUs using DEA software and the results are depicted in Table 1.

Table-1: Efficiency score of the five models

Mode	Efficiency (*DEA*)	Efficiency (*E-DEA*)	Rank (*DEA*)	Rank (*E-DEA*)
A	1	0.72	4	4
B	1	1	1	1
C	1	0.86	3	3
D	1	0.94	2	2

E	0.87	0.66	5	inefficient

From Table 1 it is observed that the models A, B, C and D are efficient and model E is only inefficient while considering DEA. Thus in this case there are only two ranks. A, B, C, and D are assigned rank 1, and E is allotted rank 5. This is leading a very poor discriminates. The reason is that each model except E performs satisfactory for at least one indicator. This is why it is desirable to bring the concept of order of efficiency through enhanced DEA. Table 1 shows that only model B is efficient and others are inefficient and ranks are assigned corresponding to each DMU introducing enhanced DEA. The rank of A, B, C, D and E is 4, 1, 3, 2 and 5 respectively. Here one DMU is efficient means the particular model performs well for each input. Here model B is most efficient and model E is least efficient. The order of efficiency is 4, 1, 3, and 2 for the respective models A, B, C and D. E is inefficient even in order 4. D is inefficient of order 1 because of cost of raw materials (with slack amount 0.12). Similarly, the model C is inefficient of orders 1 and 2 because of electricity consumption (slack amount 0.17) and cost of raw materials (slack amount 0.23). Model A is inefficient with respect number of automobiles sold (slack amount 0.26), electricity consumption (slack amount 0.11) and average wage of the workers (slack amount 0.13). Hence using enhanced DEA it is possible to rank the DMUs in a better way and also to measure the deviation from the target score (slack amount).

Now the efficiency scores obtained by using enhanced DEA are regressed with some explanatory variables. A separability condition is checked [26]. Asymptotic normal distribution is used for this purpose and the p-value corresponding to the test is 0.12. Hence the separability condition is satisfied here. In this study, a bootstrapped Tobit regression is to find influence of the size of the car, number of workers involved to produce a particular car, average period between production and sale of a car (Time lag), manager's experience, average corrective measure duration, color of most of the cars, seating capacity, air conditioning capacity on efficiency score. The categorical variables are assigned numbers for analysis purpose. For example, the cars are assigned 1,2 and 3 according to ascending order of size. Similarly the most used color is assigned 1 and 0 otherwise.

Table 2: Determinants of efficiency

Factors	Estimates	p-value
Size	-0.173	0.049
workers	1.75	0.008
Time lag	-1.07	0.041
Experience	0.89	0.032
Corrective time	-2.44	0.044
Seating capacity	-0.98	0.097
Color	0.47	0.723
A.C. capacity	2.67	0.587

Table 2 reveals the results of bootstrapped Tobit regression. Here the level of the test is taken as 0.05. Time lag between production and sale impacts negatively on efficiency. As the delay to sell the car reduces the reliability, the efficiency also declines. Number of workers is positively associated with the efficiency score. Whenever the man power is high then the manufacturing process is smoother and hence efficiency increases. Manager's experience also plays an positive significant role on the efficiency score. An experience manager can handle the quality of the product. Repair time is negatively influenced on the efficiency score. Size of the car also has negative effect on the efficiency score. The large car is less efficient. Other factors are insignificant with the efficiency scores.

5. CONCLUSION

The objective of this paper was to measure technical efficiency of various models of an automobile company based on two-dimensional warranty data and also to find out the significant determinants of efficiency scores. The study has considered five car models with the same warranty coverage. Different relevant input and output variables have been gathered from the warranty database and record of the automobile company. The analysis has been done in two steps. In the first step enhanced DEA is used to measure technical efficiency and in the second step a bootstrapped Tobit regression is applied to determine the determinants of technical efficiency. Enhanced DEA has improved the discrimination capabilities of standard DEA by introducing the concept of order of efficiency. Technical efficiency score of various automobile models shows that model B is more efficient and model E is inefficient. The inputs responsible for inefficiency of the DMUs for different orders are identified. The result of Tobit regression analysis confirms that the most influenced parameter for the input efficiency is the number of workers. Experience of manager is also an important factor. The larger sized car is lesser efficient than normal and smaller sized cars. Hence the manufacturing company has to pay more attention on different aspects of car models. The present study suggests that there is an adequate opportunity for improvement in the performance of inefficient models by choosing a correct input-output mix and selecting appropriate scale size. The findings of this study are expected to provide significant insights to policy makers for improving and optimizing usage of valuable resources in various automobile models and even different companies.

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