

**MINIMUM ABSOLUTE DEVIATION METHOD OF ESTIMATION OF
COBB-DOUGLAS FRONTIER PRODUCTION FUNCTION**

K.MUTHYALAPPA1

PROF. K.PUSHPANJALI2

DR. BR.SREEDHAR3

**1. RESEARCH SCHOLAR, DEPT. OF STATISTICS, SRI KRISHNADEVARAYA UNIVERSITY,
ANANTHAPURAMU, ANDHRA PRADESH, INDIA.**

**2. PROFESSOR, DEPT. OF STATISTICS, SRI KRISHNADEVARAYA UNIVERSITY,
ANANTHAPURAMU, ANDHRA PRADESH, INDIA.**

3. ASST. PROFESSOR, CBIT, GANDIPET, HYDERABAD, TELANGANA STATE, INDIA.

ABSTRACT

This paper contains a number of to measure technical efficiency of Decision Making Units (DMU's). This approach engages the linear programming technique (L.P.P) with parametric and non-parametric production frontiers in easy way. The parametric estimates cannot be subjected to significance tests due to the non-obtainability of standard errors (S.E's).In this Paper we proposed MAD (Minimum Absolute Deviation) method of estimation of Cobb-Douglas frontier production function as a linear programming problem (L.P.P).This method can be stretched in easy way to any parametric frontier production or cost function which is linear in parameters.

I: INTRODUCTION :-

Efficiency is critical for organizations that seek to be both environmentally conscious and profitable. Efficiency has implications for a “win-win” situation to arise. Studying and managing organizations from this perspective requires an evaluation of efficiency. To aid researchers and managers develop measures for

efficiency we review the use of data envelopment analysis (DEA) for this purpose. DEA theory and application has increased greatly. Its use as a tool for environmental performance evaluation has been limited. In this paper we provide MAD (Minimum Absolute Deviation) method of estimation of Cobb-Douglas frontier production function as a linear programming problem (L.P.P).

II INPUT LEVEL SETS:

$L(u) = \{x : x \text{ produces } u\}$, Where x, u , are input and output vectors respectively.

The input level set $L(u)$ satisfies the following properties.

1. $L(0) = R_+^n$, $0 \notin L(u)$ for $u > 0$
2. $x \in L(u)$, $x' \geq x \Rightarrow x' \in L(u)$
3. $u_2 \geq u_1 \geq 0 \Rightarrow L(u_2) \subseteq L(u_1)$

III FRONTIER PRODUCTION FUNCTION:

Let $\phi(x), x \in R_+^n$ be a frontier production function. As an optimization problem $\phi(x)$ may

be expressed as, $\phi(x) = \text{Max}\{u : x \in L(u)\}$, $0 \leq u < \infty$

$\phi(x)$ succeed properties from $L(u)$

- (i) $\phi(0) = 0$, Maximum output produced by a null input vector is zero.

$$\phi(0) = \text{Max}\{u : 0 \in L(u)\} \Rightarrow 0 \in L(u) \Rightarrow u = 0 \Rightarrow \phi(0) = 0$$

- (ii) $x' > x \Rightarrow \phi(x') \geq \phi(x)$, Maximum output produced by a larger input vector is larger.

- (iii) $\phi(x)$ is concave function of x

IV INPUT LEVEL SETS INDUCED BY A PRODUCTION FRONTIER $\phi(x)$:

$$L_\phi(u) = \{x: D(u,x) \geq 1\}, \text{ Where } D(u,x) = \left[\text{Min} \{ \lambda : \lambda x \in L(u) \} \right]^{-1} = \frac{\phi(x)}{u}$$

$$\text{It can be written } L_\phi(u) = L(u) = \left\{ x : \frac{\phi(x)}{u} \geq 1 \right\} = \{x : \phi(x) \geq u\}$$

V THE COBB-DOUGLAS PRODUCTION FRONTIER:

The Cobb-Douglas production frontier is given by,

$$\hat{y}_i = A \prod_{j=1}^n x_{ij}^{\alpha_j}, \text{ It is the } i^{\text{th}} \text{ decision making unit}$$

Taking logarithms on both sides,

$$\Rightarrow \ln \hat{y}_i = \ln A + \sum_{j=1}^n \alpha_j X_{ij} \Rightarrow \hat{Y}_i = a + \sum_{j=1}^n X_{ij} \alpha_j$$

$$\text{If } \hat{Y}_i \geq Y_i \text{ then } a + \sum_{j=1}^n X_{ij} \alpha_j \geq Y_i \quad \dots(1.1)$$

If there are k decision making units(DMUs), then $i=1,2,3,\dots,\dots,k$, Introducing slack variables s_i , Then inequation is converted equation.

$$\Rightarrow a + \sum_{j=1}^n X_{ij} \alpha_j - s_i = Y_i \Rightarrow \left[a + \sum_{j=1}^n X_{ij} \alpha_j - Y_i \right] = s_i$$

Taking summation on both sides

$$\Rightarrow \sum_{i=1}^k s_i = ka + \sum_{i=1}^k \sum_{j=1}^n X_{ij} \alpha_j - \sum_{i=1}^k Y_i \quad \dots(1.2)$$

By dividing this equation by k

$$\Rightarrow \bar{s} = a + \sum_{j=1}^n \bar{X}_j \alpha_j - \bar{Y} \quad \dots(1.3)$$

Minimization of (1.2) is same as minimization of (1.3), \bar{Y} being a constant, minimization of (1.2) is same as minimization of ,

$$\Rightarrow a + \sum_{j=1}^n \bar{X}_{.j} \alpha_j \quad \dots(1.4)$$

Combining (1.1) and (1.4) we obtain a linear programming problem (L.P.P) for which decision variables are a and α_j .

$$\begin{aligned} \text{Min } & a + \sum_{j=1}^n \bar{X}_{.j} \alpha_j \\ \text{subject to } & \\ & a + \sum_{j=1}^n X_{ij} \alpha_j \geq Y_i \\ & \alpha_j \geq 0, \text{ is conditional for sign.} \end{aligned} \quad \dots (1.5)$$

Let $a = a^+ - a^-$, the L.P.P can be expressed as follows:

$$\begin{aligned} \text{Minimize } Z &= a^+ - a^- + \sum_{j=1}^n \bar{X}_{.j} \alpha_j \\ \text{subject to } & a^+ - a^- + \sum_{j=1}^n X_{ij} \alpha_j \geq Y_i \end{aligned} \quad \dots(1.6)$$

$$a^+, a^-, \alpha_j \geq 0$$

$$i = 1, 2, 3, \dots, k$$

VI MAD METHOD OF ESTIMATION OF COBB-DOUGLAS PRODUCTION FRONTIER:

With two errors u and v , one sided and the two sided disturbance terms, then the model is given by

$$a^+ - a^- + \sum_{j=1}^n X_{ij} \alpha_j = Y_i + u_i + v_i, \text{ where } 0 \leq u_i < \infty, \quad -\infty < v_i < \infty$$

For i^{th} Decision making unit(DMU)

$$\Rightarrow a^+ - a^- + \sum_{j=1}^n X_{ij} \alpha_j - Y_i - u_i = v_i$$

Taking Modules on both sides

$$\Rightarrow \left| a^+ - a^- + \sum_{j=1}^n X_{ij} \alpha_j - Y_i - u_i \right| = |v_i| \Rightarrow a^+ - a^- + \sum_{j=1}^n X_{ij} \alpha_j - Y_i - u_i = v_i^+ + v_i^-$$

$$\text{where } v_i = v_i^+ + v_i^-, \quad v_i^+ = \text{Max}\{0, v_i\}, \quad v_i^- = -\text{Min}\{0, v_i\}$$

The optimization problem is equal to MAD estimation model and it is given by

$$\text{Min } \sum_{i=1}^k (v_i^+ + v_i^-)$$

subject to

$$a^+ - a^- + \sum_{j=1}^n X_{ij} \alpha_j - u_i - v_i^+ - v_i^- = Y_i \quad \dots(1.7)$$

$$a^+, a^-, \alpha_j, u_i, v_i^+, \text{ and } v_i^- \geq 0$$

$$i=1,2,3,\dots,m, \quad j=1,2,3,\dots,n$$

The decision variables of the above Linear Programming are A, α_j, u_i, v_i^+ and v_i^- . The optimal solution of L.P.P (1.5.1) tells DMU specific technical efficiency.

VII EFFICIENCY ESTIMATION IN COBB-DOUGLAS PRODUCTION FUNCTION USING MODIFIED LEAST SQUARES:

Consider the Cobb-Douglas production function,

$$y = A \prod_{i=1}^m x_i^{\alpha_i} u \quad \text{where } 0 \leq u \leq 1 \quad \dots(1.8)$$

Define $u = e^{-z}$; $0 < z < \infty$

Let the random variable Z follow Gamma distribution, so that,

$$f(z, \lambda) = \frac{1}{\Gamma(\lambda)} z^{\lambda-1} \exp(-z), \quad \text{where } \Gamma(\lambda) = \int_0^{\infty} z^{\lambda-1} e^{-z} dz$$

$$\ln u = -z \Rightarrow -\ln u = z \Rightarrow dz = -\frac{du}{u} \Rightarrow z = \ln\left(\frac{1}{u}\right)$$

$$z = 0 \Rightarrow u = 1, \quad z = \infty \Rightarrow u = 0$$

$$= \frac{1}{\Gamma(\lambda)} \left(\ln \frac{1}{u}\right)^{\lambda-1} du$$

The probability density function of u is given by,

$$g(u, \lambda) = \frac{1}{\Gamma(\lambda)} \left(\ln \frac{1}{u}\right)^{\lambda-1} \quad \dots (1.9)$$

Here

1. λ is shape parameter of the distribution, $g(u, \lambda)$
2. $\lambda < 1$ implies that a greater proportion of DMUs are efficient
3. $\lambda = 1$ implies uniform efficiency
4. $\lambda > 1$ implies that a greater proportion of DMUs are inefficient

The average level of efficiency of the industry comprised of several DMU is,

$$\begin{aligned} \bar{u} = E(u) &= \int_0^{\infty} \exp(-z) \frac{1}{\Gamma(\lambda)} z^{\lambda-1} \exp(-z) dz \\ &= \frac{1}{\Gamma(\lambda)} \int_0^{\infty} \exp(-2z) z^{\lambda-1} dz \quad [put 2z = v, 2dz = dv \quad dz = \frac{1}{2} dv] \\ &= \frac{1}{\Gamma(\lambda)} \int_0^{\infty} \exp(-v) \left(\frac{v}{2}\right)^{\lambda-1} 2^{-1} dv \end{aligned}$$

$$\begin{aligned}
&= \frac{2^{-\lambda}}{\Gamma(\lambda)} \int_0^{\infty} \exp(-v)(v)^{\lambda-1} dv \\
&= \frac{2^{-\lambda}}{\Gamma(\lambda)} \Gamma(\lambda) \\
\Rightarrow \bar{u} &= 2^{-\lambda}
\end{aligned}$$

VIII THE METHOD OF MODIFIED LEAST SQUARES:

Consider the Cobb-Douglas production function specification

$$y_i = A \prod_{j=1}^m x_{ij}^{\beta_j} u_i, \quad i=1,2,3,\dots,k$$

$$\begin{aligned}
\ln y_i &= \ln A + \sum_{j=1}^m \beta_j \ln x_{ij} + \ln u_i \\
\Rightarrow Y_i &= a + \sum_{j=1}^m \beta_j X_{ij} - z_i
\end{aligned}$$

....(1.10)

We have,

$$\begin{aligned}
E(z_i) &= \frac{1}{\Gamma(\lambda)} \int_0^{\infty} z_i z_i^{\lambda-1} \exp(-z_i) dz_i \\
&= \frac{1}{\Gamma(\lambda)} \int_0^{\infty} z_i^{\lambda+1-1} \exp(-z_i) dz_i \\
&= \frac{1}{\Gamma(\lambda)} \Gamma(\lambda+1) \\
&= \frac{1}{\Gamma(\lambda)} \Gamma(\lambda+1)
\end{aligned}$$

$$E(z_i) = \lambda, \quad \forall \lambda$$

$$E(z_i^2) = \frac{1}{\Gamma(\lambda)} \int_0^{\infty} z_i^{\lambda+2-1} \exp(-z_i) dz_i$$

$$= \frac{\Gamma(\lambda+2)}{\Gamma(\lambda)} = \frac{(\lambda+1)\lambda\Gamma(\lambda)}{\Gamma(\lambda)}$$

$$= \lambda(\lambda+1)$$

$$V(z_i) = E(z_i^2) - [E(z_i)]^2 = \lambda(\lambda+1) - \lambda^2$$

$$V(z_i) = \lambda, \quad \forall i$$

We shall assume that $\text{Cov}(z_j, z_l) = 0 \quad j \neq l$

Define $\alpha_0 = a - \lambda, \quad v_i = \lambda - z_i \quad \dots (1.11)$

Combine (1.7.1) and (1.7.2) to obtain,

$$\hat{y}_i = \alpha_0 + \sum_{j=1}^m \alpha_j X_{ij} + v_i$$

where $Y_i = \ln y_i, \quad X_{ij} = \ln x_{ij}$

Let v_i be an disturbance term that satisfies the following properties:

1. $E(v_i) = 0, \quad \forall i$
2. $V(v_i) = E(v_i^2) = \lambda$
3. $\text{Cov}(v_i, v_j) = 0, \quad i \neq j$
4. $E\left(\frac{v_i}{X}\right) = 0$

Under above conditions the OLS estimators are BLUE of $\alpha_0, \alpha_1, \dots, \alpha_n$. Since λ

is variance of v_i , the OLS estimator of λ is,

$$\hat{n} = \frac{\sum_{i=1}^k \left(Y_i - \hat{\alpha}_0 - \sum_{j=1}^m \hat{\alpha}_j X_{ij} \right)}{k - m - 1} \quad \dots (1.12)$$

$$E(\hat{\alpha}_0) = \alpha_0 = a - \lambda \quad \dots (1.13)$$

$$E(\hat{\alpha}_i) = \alpha_i, i = 1, 2, 3, \dots$$

$$E(\hat{\lambda}) = \lambda$$

$$E(\hat{\alpha}_0) = a - E(\hat{\lambda})$$

$$E(\hat{\alpha}_0 + \hat{\lambda}) = a \quad \dots(1.14)$$

$\hat{\alpha}_0 + \hat{\lambda}$ is an unbiased estimator of a , $2^{-\hat{\lambda}}$ is a consistent but upward biased estimator of average technical efficiency.

$$\hat{u} = 2^{-\hat{\lambda}} \quad \dots(1.15)$$

In Gamma distribution, we can estimate the proportion of DMUs with efficiency level at least equal to α

$$P[u \geq d] = P[e^{-z} \geq d] \quad \dots(1.16)$$

$$= P[z \leq -\ln d]$$

$$= \int_0^{-\ln d} \frac{1}{\Gamma(\lambda)} z^{\lambda-1} \exp(-z) dz \quad \dots(1.17)$$

References:-

1. Andersen P, Petersen NC (1993) A procedure for ranking efficient units in data envelopment analysis. *Management Science* 39: 1261-1264.
2. Azzone G, Manzini R (1994) Measuring strategic environmental performance. *Business Strategy and the Environment* 3: 1-14.

3. Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimation of technical and scale efficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092.
4. Ball VE, Lovell CAK, Nehring RF, Somwaru A. (1994) Incorporating undesirable outputs into models of production: An application to U.S. agriculture. *Cahiers d'Economie et Sociologie Rurales* 31: 59-73.
5. Brockett PL, Golany B., (1996) Using rank statistics for determining programmatic efficiency differences in data envelopment analysis. *Management Science* 42: 466-472.
6. Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. *European Journal of Operational Research* 2: 429-444.
7. Charnes A, Cooper WW, Huang ZM, Sun, DB (1990) Polyhedral cone-ratio DEA models with an illustrative application to large commercial banks. *Journal of Econometrics* 30: 91-107.
8. Conover WJ (1980) *Practical nonparametric statistics*. John Wiley & Sons, New York.
9. Cook, WD, Kress M, Seiford LM (1993) On the use of ordinal data in data envelopment analysis. *Journal of the Operational Research Society* 44: 133-140.
10. Cook WD, Kress M, Seiford, LM (1996) Data envelopment analysis in the presence of both quantitative and qualitative factors. *Journal of the Operational Research Society* 47: 945-953.

11. Corson WH (1994) Changing course : an outline of strategies for a sustainable future. *Futures* 26: 206-223.
12. Criswell DR, Thompson RG (1996) Data envelopment analysis of space and terrestrially-based large-scale commercial power systems for earth. *Solar Energy* 56: 119-131.
13. Doyle, J, Green, R (1993) Data envelopment analysis and multiple criteria decision making. *OMEGA* 21: 713-715.
14. Doyle J and Green R (1994) Efficiency and cross-efficiency in DEA: derivations, meanings and uses. *Journal of the Operational Research Society* 45: 567-578.
15. EIA (1999) Energy conversion tables. Energy Information Administration, Department of Energy, Washington, D.C. URL: www.eia.doe.gov/emeu/iea/convheat.htm.
16. Fare R, Grosskopf S, Tyteca D. (1996) An activity analysis model of the environmental performance of firms - application to fossil fuelled-fired electric utilities. *Ecological Economics and Statistics* 18: 90-98.
17. Gerde VW, Logdon JM (1999) Measuring environmental performance? Use of the toxics release inventory (TRI) and other environmental databases in business-and-society research. *Proceedings of the Tenth Annual Meeting of the International Association for Business and Society*. Paris France.
18. Grosskopf S, Valdmanis V (1987) Measuring hospital performance: a non-parametric approach. *Journal of Health Economics* 6: 89-107.

