

DERIVATION OF NORMAL – EXPONENTIAL MODEL  
FOR STOCHASTIC COST FRONTIER ANALYSIS

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(Received On: 08-06-17; Revised & Accepted On: 05-07-17)

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ABSTRACT

Stochastic Frontier Analysis in term of cost means to produce a specified level of output in a minimal possible manner. This paper provides detailed steps on the estimation of Normal Exponential model for the estimation of stochastic cost frontier. Stochastic Cost Frontier plays a major role in the estimation of Cost Efficiency Scores in the field of production. Here  $v_i \sim N(0, \sigma_v^2)$  and  $u_i \sim \text{exponential}$ . The parameters are evaluated using Maximum Likelihood Estimates. The cost efficiency of each producer can be obtained from  $CE_i = \left( e^{-\hat{u}_i} \right)$ .

**Key words:** Stochastic Frontier Analysis, Stochastic cost frontier, Cost efficiency Scores, Normal Exponential distribution, Cost efficiency scores, Maximum likelihood.

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1. INTRODUCTION

Stochastic Cost Frontier Analysis (SCFA) which began with Farrell (1957) has wide range of applications in different fields such as hospitals, banks, education sector etc. SCFA is a mathematical model to estimate cost function parameters using regression techniques. Hence comes the importance of distributional assumption. The SCFA model can be expressed as  $y_i = f(x_i, \beta) e^{v_i + u_i}$  where  $y_i$  is the output,  $x_i, \beta$  are the input and technology parameter respectively.  $v_i + u_i$  is the composed error term with  $v_i$  as the random shock and  $u_i$  captures the cost efficiency. Meeusen and Van den Broeck (1977) assigned exponential distribution to  $u_i$  and Aigner, Lovell and Schmidt (1977) considered both exponential and half normal. In this paper  $v_i$  follows normal distribution and  $u_i$  follows exponential distribution. Alijar (2014) considered truncated and exponential distribution for  $u_i$  and proposed that exponential distribution is just like half normal distribution and a special case of truncated normal distribution. In the study related to the estimation of technical efficiency of maize farmers, John Ng'ombe and Thomson Kalinda (2015) assumed exponential distribution for  $u_i$ . Maximum likelihood estimation which was developed by Aigner and Chu (1968) can be used to maximise the log likelihood function of  $f(\varepsilon)$ . Normal-Exponential Stochastic Cost Frontier Model (NESCFM) can be estimated once the conditional probability of  $u_i / \varepsilon_i$  is derived.

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**2. THE NORMAL-EXPONENTIAL STOCHASTIC COST FRONTIER MODEL (NESCFM)**

In the estimation, of  $y_i = f(x_i, \beta) e^{v_i + u_i}$

i)  $v_i \sim iid N(0, \sigma_v^2)$

ii)  $u_i \sim iid$  exponential

iii)  $v_i$  and  $u_i$  are independently and identically distributed of each other and of the regressors.

The probability density function of  $v$  is

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} e^{-\frac{v^2}{2\sigma_v^2}} \tag{1}$$

The probability density function of  $u$  is

$$f(u) = \frac{1}{\sigma_u} e^{-\frac{u}{\sigma_u}}, \text{ for } u \geq 0 \tag{2}$$

Due to the independence assumption, the joint probability density function of  $v$  and  $u$  is the product of their individual density functions therefore,

$$f(u, v) = f(u) f(v)$$

$$f(u, v) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{u}{\sigma_u} - \frac{v^2}{2\sigma_v^2}} \tag{3}$$

Taking  $\varepsilon = v + u$ , the joint probability density function of  $u$  and  $\varepsilon$  is given by

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{u}{\sigma_u} - \frac{(\varepsilon - u)^2}{2\sigma_v^2}} \tag{4}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{u}{\sigma_u} - \frac{(\varepsilon^2 - 2\varepsilon u + u)^2}{2\sigma_v^2}} \tag{5}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{u}{\sigma_u} - \frac{\varepsilon^2}{2\sigma_v^2} + \frac{2\varepsilon u}{2\sigma_v^2} - \frac{u^2}{2\sigma_v^2}} \tag{6}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{1}{2} \left[ \frac{u^2}{\sigma_v^2} - 2 \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\sigma_u} \right) u + \frac{\varepsilon^2}{\sigma_v^2} \right]} \tag{7}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{1}{2} \left[ \frac{u^2}{\sigma_v^2} - \frac{2u}{\sigma_v} \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\sigma_u} \right) + \frac{\varepsilon^2}{\sigma_v^2} \right]} \tag{8}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{1}{2} \left[ \frac{u^2}{\sigma_v^2} - \frac{2u}{\sigma_v} \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\sigma_u} \right) + \frac{\varepsilon^2}{\sigma_v^2} \right]} \tag{9}$$

Since,  $\lambda = \frac{\sigma_u}{\sigma_v}$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} e^{-\frac{1}{2} \left[ \frac{u^2}{\sigma_v^2} - \frac{2u}{\sigma_v} \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right) + \frac{\varepsilon^2}{\sigma_v^2} \right]} \tag{10}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_u \sigma_v} e^{-\frac{1}{2} \left[ \left( \frac{u}{\sigma_v} - \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right) \right)^2 - \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right)^2 + \frac{\varepsilon^2}{\sigma_v^2} \right]} \tag{11}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_u \sigma_v} e^{-\frac{1}{2} \left( \frac{u}{\sigma_v} - \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right) \right)^2} e^{-\frac{1}{2} \left( -\frac{\varepsilon^2}{\sigma_v^2} + \frac{2\varepsilon}{\sigma_v \lambda} - \frac{1}{\lambda^2} + \frac{\varepsilon^2}{\sigma_v^2} \right)} \tag{12}$$

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_u \sigma_v} e^{-\frac{1}{2} \left( \frac{u}{\sigma_v} - \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right) \right)^2} e^{\frac{1}{2} \left( \frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda} \right)} \tag{13}$$

The marginal density function of  $\varepsilon$  is given by

$$f(\varepsilon) = \int_0^\infty f(u, \varepsilon) du$$

$$f(\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_u \sigma_v} e^{\frac{1}{2} \left( \frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda} \right)} \int_0^\infty e^{-\frac{1}{2} \left( \frac{u}{\sigma_v} - \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right) \right)^2} du \tag{14}$$

Define  $\frac{u}{\sigma_v} - \left( \frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda} \right) = s$ ;  $du = \sigma_v ds$  (15)

When  $u \rightarrow 0$ ,  $s \rightarrow \frac{1}{\lambda} - \frac{\varepsilon}{\sigma_v}$ ;  $u \rightarrow \infty$ ,  $s \rightarrow \infty$

$$f(\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_u \sigma_v} e^{\frac{1}{2} \left( \frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda} \right)} \int_{\frac{1}{\lambda} - \frac{\varepsilon}{\sigma_v}}^\infty e^{-\frac{s^2}{2}} \sigma_v ds \tag{16}$$

$$f(\varepsilon) = \frac{1}{\sigma_u} e^{\frac{1}{2} \left( \frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda} \right)} \frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\lambda} - \frac{\varepsilon}{\sigma_v}}^\infty e^{-\frac{s^2}{2}} \sigma_v ds \tag{17}$$

$$f(\varepsilon) = \frac{1}{\sigma_u} e^{\frac{1}{2} \left( \frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda} \right)} \left[ 1 - \Phi \left( \frac{1}{\lambda} - \frac{\varepsilon}{\sigma_v} \right) \right] \tag{18}$$

**3. MEAN AND VARIANCE**

The marginal density function, which is asymmetrically distributed with mean and variance is given by

$$Mean = E(\varepsilon) = E(v + u) = E(u) = \int_0^\infty u f(u) du \tag{19}$$

$$E(\varepsilon) = E(u) = \int_0^\infty u \frac{1}{\sigma_u} e^{-\frac{u}{\sigma_u}} du$$

Define,  $\frac{u}{\sigma_u} = s$ ;  $du = \sigma_u ds$

$s$  varies from 0 to  $\infty$

Therefore,  $E(u) = \frac{1}{\sigma_u} \int_0^\infty \sigma_u s e^{-s} \sigma_u ds$ . (20)

$$E(u) = \sigma_u \left[ s e^{-s} (-1) - e^{-s} \right]_0^\infty \tag{21}$$

$$E(u) = \sigma_u (1) = \sigma_u \tag{22}$$

To find Variance,  $v(\varepsilon) = v(v) + v(u)$

$$V(u) = E(u^2) - (E(u))^2 \tag{23}$$

$$E(u^2) = \int_0^\infty u^2 f(u) du$$

$$= \int_0^\infty u^2 \frac{1}{\sigma_u} e^{-\frac{u}{\sigma_u}} du \tag{24}$$

Again let,  $\frac{u}{\sigma_u} = s ; du = \sigma_u ds ; u^2 = \sigma_u^2 s^2$

$s$  varies from 0 to  $\infty$

Hence,  $E(u^2) = \frac{1}{\sigma_u} \int_0^\infty \sigma_u^2 s^2 e^{-s} \sigma_u ds$  (25)

$$E(u^2) = \frac{\sigma_u^3}{\sigma_u} \int_0^\infty s^2 e^{-s} ds \tag{26}$$

$$E(u^2) = \sigma_u^2 [s^2(-e^{-s}) - 2s(e^{-s}) + 2s(-e^{-s})]_0^\infty \tag{27}$$

$$E(u^2) = \sigma_u^2 [0 - 2(0 - 1)] = 2\sigma_u^2 \tag{28}$$

$$v(u) = 2\sigma_u^2 - \sigma_u^2 = \sigma_u^2 \text{ and } v(v) = \sigma_v^2 \tag{29}$$

$$v(\varepsilon) = \sigma_v^2 + \sigma_u^2 \tag{30}$$

The product of the density function of the individual observations is the likelihood function of the sample, which is given as,

$$L(\text{sample}) = \prod_{i=1}^{i=k} f(\varepsilon_i)$$

The log likelihood equation for a sample of K producers is

$$\ln L = -\frac{k}{2} (\ln \sigma_u^2) + \sum_{i=1}^k \ln \left[ 1 - \Phi \left( \frac{1}{\lambda} - \frac{\varepsilon_i}{\sigma_v} \right) \right] + \frac{k}{2\lambda^2} - \sum_{i=1}^k \frac{\varepsilon_i}{\sigma_v \lambda} \tag{31}$$

Let  $\varepsilon_i = y_i - \beta' x_i$

$$\ln L = -\frac{K}{2} (\ln \sigma_u^2) + \sum_{i=1}^K \ln \left[ 1 - \Phi \left( \frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v} \right) \right] + \frac{K}{2\lambda^2} - \sum_{i=1}^K \frac{(y_i - \beta' x_i)}{\sigma_v \lambda} \tag{32}$$

Using loglikelihood function, cost efficiency can be measured after the parameter estimation.

#### 4. ESTIMATION OF THE PARAMETERS OF THE NORMAL-EXPONENTIAL STOCHASTIC COST FRONTIER MODEL

Parameters  $\sigma_u^2, \sigma_v^2, \lambda^2, \beta$  can be estimated using the first order conditions of the maximization of log-likelihood function of (32) as follows.

$$E^* \sigma_u^2 = \frac{\partial \ln L}{\partial \sigma_u^2} = -\frac{K}{2} \frac{1}{\sigma_u^2} = 0 \tag{33}$$

$$E^* \sigma_v^2 = \frac{\partial \ln L}{\partial \sigma_v^2} = \frac{1}{2\lambda} \sum_{i=1}^K \frac{y_i - \beta' x_i}{\sigma_v^3} - \frac{1}{2\lambda \sigma_v^3} \sum_{i=1}^K \frac{\phi \left( \frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v} \right)}{1 - \Phi \left( \frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v} \right)} (y_i - \beta' x_i) = 0 \tag{34}$$

$$E^* \beta = \frac{\partial \ln L}{\partial \beta} = \sum_{i=1}^K \frac{\phi\left(\frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v}\right)}{1 - \Phi\left(\frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v}\right)} \left(\frac{x_i}{\sigma_v}\right) + \sum_{i=1}^K \frac{x_i}{\sigma_v \lambda} = 0 \quad (35)$$

$$E^* \lambda^2 = \frac{\partial \ln L}{\partial \lambda^2} = -\frac{k}{2\lambda^4} + \frac{1}{2\lambda^3} \sum_{i=1}^K \frac{\phi\left(\frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v}\right)}{1 - \Phi\left(\frac{1}{\lambda} - \frac{(y_i - \beta' x_i)}{\sigma_v}\right)} (y_i - \beta' x_i) = 0 \quad (36)$$

Once the parameters are estimated the inefficiency,  $u_i$  can be obtained. In order to extract the information that  $\varepsilon_i$  contains on  $u_i$  can be done using the conditional distribution of  $u_i$  given  $\varepsilon_i$  .(Kumbhakar et al. 2003). The conditional distribution of  $u_i$  given  $\varepsilon_i$  when  $u_i$  follows half normal distribution is given by Jondrow *et al.*(1982), same condition can be used when  $u_i$  is assumed with exponential distribution.

$$f(u/\varepsilon) = \frac{f(u, \varepsilon)}{f(\varepsilon)}$$

$$f(u/\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_u \sigma_v} e^{-\frac{1}{2}\left(\frac{u}{\sigma_v} - \left(\frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda}\right)\right)^2} e^{\frac{1}{2}\left(\frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda}\right)}$$

$$f(u/\varepsilon) = \frac{1}{\sigma_u} e^{\frac{1}{2}\left(\frac{1}{\lambda^2} - \frac{2\varepsilon}{\sigma_v \lambda}\right)} \left[1 - \Phi\left(\frac{1}{\lambda} - \frac{\varepsilon}{\sigma_v}\right)\right] \quad (37)$$

$$f(u/\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[1 - \Phi\left(\frac{1}{\lambda} - \frac{\varepsilon}{\sigma_v}\right)\right]^{-1} e^{-\frac{1}{2}\left(\frac{u}{\sigma_v} - \left(\frac{\varepsilon}{\sigma_v} - \frac{1}{\lambda}\right)\right)^2} \quad (38)$$

$$f(u/\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[1 - \Phi\left(\frac{1}{\frac{\sigma_u}{\sigma_v}} - \frac{\varepsilon}{\sigma_v}\right)\right]^{-1} e^{-\frac{1}{2}\left(\frac{u}{\sigma_v} - \left(\frac{\varepsilon}{\sigma_v} - \frac{1}{\frac{\sigma_u}{\sigma_v}}\right)\right)^2} \quad (39)$$

$$f(u/\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[1 - \Phi\left(\frac{\sigma_v^2}{\sigma_u \sigma_v} - \frac{\varepsilon}{\sigma_v}\right)\right]^{-1} e^{-\frac{1}{2}\left(\frac{u}{\sigma_v} - \left(\frac{\varepsilon}{\sigma_v} - \frac{\sigma_v^2}{\sigma_u \sigma_v}\right)\right)^2} \quad (40)$$

$$f(u/\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[1 - \Phi\left(-\left\{\frac{\varepsilon}{\sigma_v} - \frac{\sigma_v^2}{\sigma_u \sigma_v}\right\}\right)\right]^{-1} e^{-\frac{1}{2\sigma_v}\left(u - \left(\varepsilon - \frac{\sigma_v^2}{\sigma_u}\right)\right)^2} \quad (41)$$

Let  $\hat{\mu} = \varepsilon - \frac{\sigma_v^2}{\sigma_u}$

$$f(u/\varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[1 - \Phi\left(-\frac{\hat{\mu}}{\sigma_v}\right)\right]^{-1} e^{-\frac{1}{2\sigma_v}\left(u - \hat{\mu}\right)^2} \quad (42)$$

**5. MEASURE OF COST EFFICIENCY OF NORMAL-EXPONENTIAL STOCHASTIC COST FRONTIER MODEL**

As  $f(u / \varepsilon)$  is distributed as  $N^+(\hat{\mu}, \sigma_v^2)$ , the mean of this distribution can serve as a point estimator of  $u_i$  which is given by

$$E(u / \varepsilon) = \int_0^{\infty} u f(u / \varepsilon) du \tag{43}$$

$$E(u / \varepsilon) = \int_0^{\infty} u \frac{1}{\sqrt{2\pi} \sigma_v} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} e^{-\frac{1}{2\sigma_v} (u - \hat{\mu})^2} du \tag{44}$$

$$E(u / \varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \int_0^{\infty} u e^{-\frac{1}{2\sigma_v} (u - \hat{\mu})^2} du \tag{45}$$

Let  $s = \frac{u - \hat{\mu}}{\sigma_v}$ ;  $u = s\sigma_v + \hat{\mu}$ ;  $du = \sigma_v ds$ .

$s$  varies from  $-\frac{\hat{\mu}}{\sigma_v}$  to  $\infty$

$$E(u / \varepsilon) = \frac{1}{\sqrt{2\pi} \sigma_v} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \int_{-\frac{\hat{\mu}}{\sigma_v}}^{\infty} (s\sigma_v + \hat{\mu}) e^{-\frac{s^2}{2}} \sigma_v ds \tag{46}$$

$$E(u / \varepsilon) = \frac{1}{\sqrt{2\pi}} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \left\{ \sigma_v \int_{-\frac{\hat{\mu}}{\sigma_v}}^{\infty} s e^{-\frac{s^2}{2}} ds + \hat{\mu} \int_{-\frac{\hat{\mu}}{\sigma_v}}^{\infty} e^{-\frac{s^2}{2}} ds \right\} \tag{47}$$

$$E(u / \varepsilon) = \frac{1}{\sqrt{2\pi}} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \sigma_v \left( e^{-\frac{s^2}{2}} (-1) \right)_{-\frac{\hat{\mu}}{\sigma_v}}^{\infty} + \hat{\mu} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \frac{1}{\sqrt{2\pi}} \int_{-\frac{\hat{\mu}}{\sigma_v}}^{\infty} e^{-\frac{s^2}{2}} ds \tag{48}$$

$$E(u / \varepsilon) = \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \sigma_v \frac{1}{\sqrt{2\pi}} e^{-\frac{\hat{\mu}^2}{2\sigma_v^2}} + \hat{\mu} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \frac{1}{\sqrt{2\pi}} \int_{-\frac{\hat{\mu}}{\sigma_v}}^{\infty} e^{-\frac{s^2}{2}} ds \tag{49}$$

$$E(u / \varepsilon) = \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \sigma_v \phi \left( \frac{\hat{\mu}}{\sigma_v} \right) + \hat{\mu} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]^{-1} \left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right] \tag{50}$$

$$E(u / \varepsilon) = \hat{\mu} + \frac{\sigma_v \phi \left( \frac{\hat{\mu}}{\sigma_v} \right)}{\left[ 1 - \Phi \left( -\frac{\hat{\mu}}{\sigma_v} \right) \right]} \tag{51}$$

## 6. CONCLUSION

Once the marginal density function of  $\varepsilon_i$  is calculated, using log likelihood functions,  $\sigma_u^2, \sigma_v^2, \lambda^2, \beta$  are estimated. The cost efficiency of each producer can be obtained from  $CE_i = (e^{-\hat{u}_i})$ , where  $\hat{u}_i = E(u_i/\varepsilon_i)$ . If an organisation uses its resources allocatively and technically efficient then it can be said that it has achieved cost efficiency. We may apply the models to real data sets to get the cost efficiencies for each producers. Similarly, we can estimate the parameters for other distributions and derive cost efficiency. According to the value of the loglikelihood function of each model, we can conclude which model is better. Analysis of the collected data can be done using LIMDEP software.

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**Source of support: Nil, Conflict of interest: None Declared.**

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