



# Maximum Likelihood Estimation in the Presence of Errors in Variables: A Modified Approach

**KEYWORDS**

Parameter, Errors in Variables, Maximum Likelihood estimator (M.L.E), Mean Square Error (MSE).

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**ABSTRACT** *In general, most of the measurements employed in economic analysis contain sizeable errors of measurement. Any realistic model must take this fact in to consideration. In the presence of measurement errors, the OLS Method of estimation of parameters of the general linear model breaks down. Maximum Likelihood (M.L) method assumes error variances to be known. Even if it is taken that the error variances are known, the variance covariance matrix of true variables thus obtained using covariance matrix of error variables, need not necessarily be positive definite. This paper discusses how to get the M.L estimator of covariance matrix of true variables which is positive definite matrix and hence obtain the modified M.L estimator of the parameter vector. It is also found that the modified M.L Estimator is better than the OLE from the point of view of bias and Mean Square Error (MSE).*

**INTRODUCTION**

Let there be a general model with stochastic regressors

$$Y = X \beta + \epsilon \tag{1.1}$$

n.1 n.k k.1 n.1

when there are errors in variables, then,  $y, x_j$  ( $j=1, \dots, k$ ) are known as true variables and the observed variables are  $y^*, x_j^*$ , with additive errors  $v$  and  $z$ .

$$y^* = y + v$$

$$x^* = x + z \tag{1.2}$$

Under the usual assumptions of errors in variables model, there exists an observed model

$$Y^* = X^* \beta^* + \epsilon^* \tag{1.3}$$

Corresponding to (1.1) [Refer: Lindley (1947)]

For all practical purposes of estimation and testing one has to depend on the observed model, (1.3), since true variables are not known.

It is well known that OLS method breakdown in the sense that it cannot provide even consistent estimators of parameter vector  $\beta$  [Johnston (1963)].

There is voluminous literature on the topic suggesting different methods of estimation of parameters of true model. However, there is no satisfactory solution.

Making use of the correspondence between true model (1.1) and observed model (1.3) a new estimator is provided, which is a linear transform of the OLS,  $\hat{\beta}^*$ , based on the observed model.

This new estimator is

$$b = \tilde{M}_x^{-1} \hat{M}_{x^*y^*} \tag{1.4}$$

Where,  $M_{xx}, M_{xy}, M$  and  $M_{x^*y^*}$  are the variance covariance matrices of  $x_j, x_j, (x_j, z)$  and  $(x_j^*, y^*)$  respectively, whose sample estimators are given by

$$\hat{M}_{x^*} = \left( \frac{x^{*T} x^*}{n} \right) \tag{1.5}$$

$$\hat{M}_x = \left( \frac{x^T x}{n} \right)$$

$$\hat{M} = \frac{x^T z + z^T x + z^T z}{n}$$

$$\hat{M}_{x^*y^*} = \left( \frac{x^{*T} y^*}{n} \right)$$

and the asymptotic variance covariance matrix of  $b$  is obtained as

$$\sigma^2 M_x^{-1} M_{x^*} M_x^{-1} \tag{1.6}$$

[Refer: V. B. Naidu et al 1992].

However, the same estimator can also be obtained without making use of the correspondence between true model and observed model. But there is some definite advantage in assuming the correspondence between the models.

It is clear from the discussion, that  $\hat{M}_{x^*}$  and  $\hat{M}_{x^*y^*}$  alone can be computed in practice, directly and they are M.L. estimators. If  $M$  is known,  $b$  is nothing but M.L. estimator of  $\beta$  provided  $M_x$  is positive matrix [Refer, Judge, C.J. et al. (1980)].

However, since,  $x_j^* = x_j + z_j, M_{x^*} = M_x + M$  and hence  $\tilde{M}_x = \tilde{M}_{x^*} - M$  and it is an unbiased estimator of  $M_x$ . But it is not certain that  $\tilde{M}_x$  thus obtained is positive definite and much less whether it is M.L. estimator of  $M_x$ . More often, in economic situations,  $M$  has to be chosen from extraneous information in which case it is not admissible in general as a covariance matrix. And hence,  $b$ , can no longer be M.L. estimator. Now the question is can we have M.L. estimator of  $M_x$ , which is positive definite? In this article an attempt is made to answer this question.

There are certain procedures developed to provide general method of analysis of covariance structures. In cases analytical solutions are not possible to get maximum likelihood estimators of covariance matrix numerical maximization of likelihood functions are proposed to provide maximum likelihood estimators of covariance matrix, under multivariate normality assumption of explanatory variables, along with imposed conditions on the nature of parameter matrix [Ref: Bock, R.D. and Bergman, R.D. (1966), Fletcher, R and Powell, N.J.D. (1963), Wiley D.W. et al., (1975)].

The basic problem is, it is given that,  $M_{x^*} = M_x + M$ , where  $M_{x^*}$ ,  $M_x$  are positive definite and  $M$  is symmetric matrix and further M.L. estimator of  $M_{x^*}$  is  $\hat{M}_{x^*}$ . Using this information, if  $M$  is known, can we arrive at M.L. estimator of  $M_x$ , which is positive definite?

**RESULT**

There exists a matrix  $P$  such that  $P^1 M_x P = D_2$ , a diagonal matrix with positive elements.

Proof: We have  $\hat{M}_{x^*} = \tilde{M}_x + M$  ( $M$  known)

It is given that  $\hat{M}_{x^*}$  is positive definite and  $M$  is symmetric. Then there is a standard matrix algebra result, which says that, there exists a matrix  $P$  such that  $P^1 \hat{M}_{x^*} P = I$ , and

$P^1 M P = D_1$  (diagonal matrix) with  $D_{1i} > 0$ .

$$\therefore P^1 \hat{M}_{x^*} P = P^1 \tilde{M}_x P + P^1 M P \tag{1.7}$$

$$P^1 \tilde{M}_x P = P^1 \hat{M}_{x^*} P - P^1 M P \tag{1.8}$$

$$\text{i.e. } D_2 = (I - D_1) \tag{1.9}$$

where  $D_2$  is a diagonal matrix. If  $D_2$  is to be positive definite,  $D_2$  must be a diagonal matrix with positive elements i.e.

$$D_{2i} = (1 - D_{1i}) > 0 \tag{1.10}$$

which implies that  $D_{1i} < 1$ , and it is possible to have such  $D_{1i}$ . Hence the result.

From (1.8)

$$\text{Consider, } P^1 \tilde{M}_x P = P^1 \hat{M}_{x^*} P - P^1 M P$$

$$\text{i.e., } \tilde{M}_x = Q' (I - D_1) Q, \tag{1.11}$$

where  $Q = P^1$

$$\text{From (1.11) we have } \hat{M}_x = Q' (I - D_1^*) Q \tag{1.12}$$

Where  $D_1^* = \text{diag}(D_{1i}; 0 < D_{1i} < 1)$  is a positive definite and it is M.L. estimator of  $M_x$ .

[Ref: Bock R.D. and Vandenberg, S.G. (1968)].

Thus the modified maximum likelihood estimator of  $\beta$  can be obtained by

$$\hat{\beta} = [Q' (I - D_1^*) Q]^{-1} \hat{M}_{x^*} y^* \tag{1.13}$$

In classical M.L. estimation of  $\beta$  vector the variance covariance of the estimator is not given. However, following the correspondence between the true model and observed model, we can have from (1.6) the asymptotic variance covariance matrix of  $\beta$  as

$$\text{Asy } v(\hat{\beta}) = \sigma^2 M_x^{-1} M_{x^*} M_x^{-1}$$

and an estimator of it is given by

$$\text{Estimated Asy } v(\hat{\beta}) = \hat{\sigma}^2 \hat{M}_x^{-1} \hat{M}_{x^*} \hat{M}_x^{-1} \tag{1.14}$$

**MONTE CARLO STUDY**

To study the behaviour of the modified approach of M L pro-

cedure in the presence of errors in variables linear model, the following experiment is designed

$$\text{The model considered as } Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \tag{1.15}$$

Where  $y^* = y + v$

$$x_j^* = x_j + z_j, \quad j = 1, 2, 3 \dots$$

Where  $y$  and  $x_j$  and true variables,  $y^*$ ,  $x_j^*$  and observed variables with errors  $v$  and  $Z$ . The efficiency of the modified M L estimator is examined for the following case where all the variables follow normal distribution.

$$X_j \sim N(0, 1)$$

$$Z_j \sim N(0, 0.1), \quad j = 1, 2, 3 \dots \tag{1.16}$$

and  $V \sim N(0, 0.1)$

Further in the above case the following two parameters structures are considered

$$(i) \beta_1 = 0.01, \quad \beta_2 = 0.3 \quad \beta_3 = 0.6 \tag{1.17}$$

$$(ii) \beta_1 = -0.3, \quad \beta_2 = 3.0 \quad \beta_3 = 6.0 \tag{1.18}$$

with the parameter structures (1.17), (1.18) and the observation generated on  $X_j$  ( $j=1, 2, 3, \dots$ ), the observations on the dependent variables  $Y$  are obtained by using the relation (1.15). Errors  $Z$  and  $V$  are introduced into the variables  $X_j$  and  $Y$  according to the relation (1.16).

50 sets of samples of size 10, 20, 30, 50 and 100 considered in computing the estimator in each of the two different structures.

$$\text{The modified M L estimator is } \hat{\beta} = [Q' (I - D_1^*) Q]^{-1} \hat{M}_{x^*} y^* \tag{1.19}$$

The measure of efficiency of the new estimator to that of OLE with errors viz.,

$$e = \frac{|\text{MSE}(\hat{\beta}^*)|}{|\text{MSE}(\hat{\beta})|} \text{ is provided.}$$

Table-1, represents measure of efficiency of structure-I and structure-II

**TABLE-1  
MEASURE OF EFFICIENCY**

Sample size	Structure-I	Structure-II
10	10 <sup>2</sup> (0.301459)	10 <sup>3</sup> (0.532870)
20	10 <sup>4</sup> (0.837204)	10 <sup>2</sup> (0.247035)
30	10 <sup>5</sup> (0.143926)	10 <sup>6</sup> (0.159920)
50	10 <sup>6</sup> (0.492883)	10 <sup>4</sup> (0.648397)
100	10 <sup>9</sup> (0.275319)	10 <sup>7</sup> (0.394682)

**SUMMARY OF THE RESULTS**

From the Monte Carlo study the following observations are made.

1. The bias in the modified M L estimation is less than the bias in OLE
2. For the two structures the value of  $e > 1$ , implying that the modified M L estimator is more efficient than OLE

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