

# An Efficient Estimator for Estimating Population Variance in Presence of Measurement Errors

Research Article

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**Abstract:** The present paper advocates the problem of estimating population variance when the measurement errors are present in both the study variable and the auxiliary variable. Bias and Mean Square Error (MSE) of the proposed estimator is obtained up to first order of approximation. Theoretical efficiency comparison between usual variance estimator and the proposed estimator is also made under measurement errors. Theoretical results are supported by simulation study using R software.

**Keywords:** Variance, Measurement Errors, Bias, MSE, Efficiency, Simulation, R software.

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## 1. Introduction

Most of the statistical procedures for the data analysis assume that the observations on the characteristic of interest are recorded without any error. But in real life such assumptions are not valid and data is contaminated with measurement errors due to various reasons [1, 2, 4]. When observations are subject to measurement errors then the estimates of population parameters (Mean, Variance, Total etc.) based on that values leads to the incorrect estimates. So the study of these errors is much needed.

Measurement errors play a very significant role especially in surveys which are related with socially undesirable characteristics and may mislead in conclusions if not handled properly. Measurement errors arise in data collection or taking observations and are mainly contributed by the respondent or the enumerator or both. Measurement errors refer to the discrepancy between the individual true value and the corresponding observed sampling value irrespective of reasons for discrepancies. Since these errors arise at the time of observation taking process so sometimes these are also known as observational errors. Responses of interviewers are also one of the reasons of these errors, so these are also known as Response errors. Measurement errors or observational errors are sometimes called as accommodation errors.

Measurement errors are generally taken as normally distributed with mean zero implies that average effect of measurement errors on respondents answer is zero, chapter 1 by M. Groves ([6]). But it will increase the variability, so estimation of these errors needs a wide attention. Many authors including Das [17], Srivastava [15], Singh [8] and Diana [18], studied the effects of measurement errors on estimation of population parameters. In the present article we are focusing upon the study of estimation of population variance when the observations are subject to measurement errors.

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## 2. Estimation of Population Variance Under Measurement Errors

Let us assume that  $Y$  and  $X$  are the study and auxiliary variables defined on a finite population  $U = \{U_1, U_2, \dots, U_N\}$  of size  $N$  and a sample of size  $n$  is drawn by simple random sampling without replacement (SRSWOR) on these two characteristics  $Y$  and  $X$ . Here it is assumed that  $y_i$  and  $x_i$  are observed instead of true values  $Y_i$  and  $X_i$  respectively. The measurement errors are defined as

$$u_i = y_i - Y_i \quad (1)$$

$$v_i = x_i - X_i \quad (2)$$

$u_i$  and  $v_i$  are random in nature with mean zero and different variances  $\sigma_u^2$  and  $\sigma_v^2$  respectively. It is assumed that  $u_i$ 's and  $v_i$ 's are uncorrelated although  $Y_i$ 's and  $X_i$ 's are correlated. It is also assumed that  $u_i$ 's and  $v_i$ 's are uncorrelated with  $Y_i$ 's and  $X_i$ 's respectively. Let  $(\mu_Y, \mu_X)$  and  $(\sigma_Y^2, \sigma_X^2)$  are mean and variances of  $(Y, X)$ , i.e., study and auxiliary variables.  $\rho$  is the correlation coefficient between  $X$  and  $Y$ . Let  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$ ,  $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$  be the unbiased estimators of the population means  $\mu_Y$  and  $\mu_X$  respectively.

$$s_x^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

and

$$s_y^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$$

are not unbiased estimators of the population variances  $\sigma_X^2$  and  $\sigma_Y^2$ . In presence of measurement errors the expected value of  $s_y^2$  and  $s_x^2$  is given by  $E(s_y^2) = \sigma_Y^2 + \sigma_u^2$  and  $E(s_x^2) = \sigma_X^2 + \sigma_v^2$ . Let error variances  $\sigma_u^2$  and  $\sigma_v^2$  are known a priori than unbiased estimators of population variance under measurement errors are

$$\hat{\sigma}_Y^2 = s_y^2 - \sigma_u^2 > 0$$

$$\hat{\sigma}_X^2 = s_x^2 - \sigma_v^2 > 0$$

Now, let us define

$$\hat{\sigma}_Y^2 = \sigma_Y^2(1 + e_0)$$

$$\bar{x} = \mu_X(1 + e_1)$$

$$E(e_0) = E(e_1) = 0$$

$$E(e_0^2) = \frac{A_y}{n}$$

$$E(e_1^2) = \frac{C_X^2}{n\theta_X}$$

$$E(e_0e_1) = \frac{\delta C_X}{n}$$

Where,

$$A_y = \gamma_{2Y} + \gamma_{2u} \frac{\sigma_u^2}{\sigma_Y^2} + 2\left(1 + \frac{\sigma_u^2}{\sigma_Y^2}\right)^2$$

$$\theta_x = \frac{\sigma_X^2}{\sigma_X^2 - \sigma_v^2}$$

$$\delta = \frac{\mu_{12}(X, Y)}{\sigma_X \sigma_Y^2}$$

$$\gamma_{2z} = \beta_{2z} - 3,$$

$$\begin{aligned}\beta_{2z} &= \mu_{4z}/(\mu_{2z}^2) \text{ and} \\ \mu_{rz} &= E(z_i - \mu_z)^2; \\ z &= X, Y, U, V \\ \mu_{22}(XY) &= E\{(X_i - \mu_X)^2(Y_i - \mu_Y)^2\}\end{aligned}$$

The usual unbiased estimator of the population variance of the study variable Y under measurement errors is defined by

$$\begin{aligned}t_0 &= \hat{\sigma}_y^2 \\ &= \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2\end{aligned}\tag{3}$$

$$Bias(t_0) = 0\tag{4}$$

$$MSE(t_0) = \sigma_Y^4 \frac{A_y}{n}\tag{5}$$

### 3. Suggested Estimator

$$\begin{aligned}t_k &= \hat{\sigma}_y^2 \left[1 + k \frac{(\bar{x} - \mu_X)}{\mu_X}\right] \\ &= \sigma_y^2 (1 + e_0) \left[1 + k \frac{(\mu_x(1 + e_0) - \mu_x)}{\mu_x}\right] \\ &= \sigma_y^2 (1 + ke_1 + e_0 + ke_0e_1)\end{aligned}\tag{6}$$

$$(t_k - \sigma_y^2) = \sigma_y^2 (ke_1 + e_0 + ke_0e_1)\tag{7}$$

$$Bias(t_k) = \sigma_y^2 k E(e_0e_1)$$

$$Bias(t_k) = \sigma_y^2 k \frac{\delta C_X}{n}\tag{8}$$

hence

$$Bias(t_k) = \frac{\mu_{12}(X, Y)}{n\mu_x}$$

Which is of order  $O(1/n)$ , hence the bias of estimator  $t_k$  is negligible for sufficient large value of n, and for symmetrical population bias becomes zero for the order of our approximation. Squaring Equation (7) both sides, we get

$$\begin{aligned}(t_k - \sigma_y^2)^2 &= \sigma_y^4 [ke_1 + e_0 + ke_0e_1]^2 \\ &= \sigma_y^4 [k^2 e_1^2 + e_0^2 + k^2 e_0^2 e_1^2 + 2ke_0e_1 + 2k^2 e_0 e_1^2 + 2ke_1 e_0^2]\end{aligned}$$

Taking expectation on both sides and ignoring terms of higher order we get the mean square error (MSE)

$$\begin{aligned}&= E(t_k - \sigma_y^2)^2 = \sigma_y^4 E[k^2 e_1^2 + e_0^2 + 2ke_0e_1] \\ E(t_k - \sigma_y^2)^2 &= \sigma_y^4 [k^2 E(e_1^2) + E(e_0^2) + 2kE(e_0e_1)]\end{aligned}$$

Substituting the values of  $E(e_0^2)$ ,  $E(e_1^2)$  and  $E(e_0e_1)$  we get

$$MSE(t_k) = \frac{\sigma_y^4}{n} \left[ k^2 \frac{C_X^2}{\theta_X} + A_Y + 2k\lambda C_x \right]$$

$$MSE(t_k) = \frac{\sigma_y^4}{n} \left[ k^2 C_X^2 \left( 1 + \frac{\sigma_v^2}{\sigma_X^2} \right) + A_Y + 2k\lambda C_x \right] \quad (9)$$

Now the optimum value of  $k$  is

$$k = -\lambda \frac{\theta_X}{C_X} \quad (10)$$

Hence minimum MSE is obtained by substituting the value of  $k$  in (9)

$$\begin{aligned} MSE(t_k)_{\min} &= \frac{\sigma_Y^4}{n} (2 + \gamma_Y^2) + \frac{\sigma_Y^4}{n} \frac{\sigma_u^2}{\sigma_Y^4} (2 + \gamma_u^2) + 4 \frac{\sigma_u^2}{\sigma_Y^2} - \lambda^2 \left( \frac{\sigma_X^2}{\sigma_v^2 + \sigma_X^2} \right) \\ &= \text{Sampling variance } (V_1) + \text{Measurement variance } (V_2) \end{aligned} \quad (11)$$

where  $V_1 = \frac{\sigma_Y^4}{n} (2 + \gamma_Y^2)$  and  $V_2 = \frac{\sigma_Y^4}{n} \left[ \frac{\sigma_u^2}{\sigma_Y^4} (2 + \gamma_u^2) + 4 \frac{\sigma_u^2}{\sigma_Y^2} - \lambda^2 \left( \frac{\sigma_X^2}{\sigma_v^2 + \sigma_X^2} \right) \right]$ .

## 4. Efficiency Comparison with Usual Unbiased Estimator

Proposed estimator will be more efficient than the usual unbiased estimator iff  $MSE(t_k)_{\min} - MSE(t_0) < 0$  which provides

$$\lambda^2 \left( \frac{\sigma_X^2}{\sigma_v^2 + \sigma_X^2} \right) > 0 \quad (12)$$

Our proposed estimator  $t_k$  will be more efficient than the usual unbiased variance estimator  $t_0$  if the condition (12) is satisfied by the data set.

## 5. Simulation Study

In this section, we demonstrate the performance of adopted estimator over the usual variance estimator in presence of measurement errors, generating population from normal distribution by using R programme. The description of this data is as follows  $X = N(5, 10)$ ,  $Y = X + N(0, 1)$ ,  $y = Y + N(1, 3)$ ,  $x = X + N(1, 3)$ ,  $n = 5000$ ,  $\mu_X = 4.95$ ,  $\mu_Y = 4.93$ ,  $\sigma_X^2 = 99.38$ ,  $\sigma_Y^2 = 100.12$ ,  $\sigma_u^2 = 25.57$ ,  $\sigma_v^2 = 24.28$ ,  $\rho_{XY} = 0.99$ . By using these values we find that the condition (12) is satisfied by the above data set. So our proposed estimator will be more efficient than the usual unbiased estimator. Now the MSE's of both estimators are given as

$$MSE(t_k)_{\min} = 6.01$$

$$MSE(t_0) = 6.25$$

## 6. Concluding Remarks

- Since the expression of Bias does not involve  $\sigma_u^2$  or  $\sigma_v^2$  so Bias of the proposed estimator is not affected by the measurement errors.
- Since  $MSE(t_k)_{\min} < MSE(t_0)$  so our proposed estimator is more efficient than the usual unbiased estimator in presence of measurement errors.

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