5-1-2015

Method of Estimation in the Presence of Non-response and Measurement Errors Simultaneously

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The problem of estimating the finite population mean of in simple random sampling in the presence of non-response and response error was considered. The estimators use auxiliary information to improve efficiency, assuming non–response and measurement error are present in both the study and auxiliary variables. A class of estimators was proposed and its properties studied in the simultaneous presence of non-response and response errors. It was shown that the proposed class of estimators is more efficient than the usual unbiased estimator, ratio and product estimators under non-response and response error together. A numerical study was carried out to compare its performance.

Keywords: Population mean, Study variable, Auxiliary variable, Mean squared error, Measurement errors, Non-response.

Introduction

Over the past several decades, statisticians were interested in the problem of estimating the parameters of interest in the presence of response error (measurement errors). In survey sampling the properties of the estimators based on data usually presuppose that the observations are the correct measurements on characteristics being studied. However, this assumption is not satisfied in many applications and data is contaminated with measurement errors, such as reporting errors and computing errors. These measurement errors make the result invalid, which are meant for no measurement error case. If measurement errors are very small and we can neglect it, then the statistical inferences based on observed data continue to remain valid. On the contrary, when they are not appreciably small and negligible, the inferences may not be simply invalid and inaccurate but may

often lead to unexpected, undesirable and unfortunate consequences (see Srivastava & Shalabh 2001). Some important sources of measurement errors in survey data are discussed in Cochran (1968), Shalabh (1997), Sud and Srivastva (2000). Singh and Karpe (2008, 2010), Kumar, Singh, and Smarandache (2011), Kumar, Singh, Sawan, and Chauhan (2011) and Sharma and Singh (2013) studied the properties of some estimators of population parameters under measurement error.

Consider a finite population $U = (U_1, U_2,..., U_N)$ of N units. Let Y and X be the study variate and auxiliary variate, respectively. Suppose that we have a set of n paired observations obtained through simple random sampling procedure on two characteristics X and Y. Further it is assumed that x_i and y_i for the ith sampling units are observed with measurement error instead of their true values (X_i, Y_i). For a simple random sampling scheme, let (x_i, y_i) be observed values instead of the true values (X_i, Y_i) for i^{th} $(i = 1.2, ..., n)$ unit, as

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

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

where u_i and v_i are associated measurement errors which are stochastic in nature with mean zero and variances σ_u^2 and σ_v^2, respectively. Further, let the u_i's and v_i's are uncorrelated although X_i's and Y_i's are correlated.

Let the population means of X and Y characteristics be μ_x and μ_y, population variances of (x, y) be (σ_x^2, σ_y^2) and let ρ be the population correlation coefficient between x and y respectively (see Manisha and Singh 2002).

In sample surveys, the problem of non-response is common and is more widespread in mail surveys than in personal interviews. The usual approach to overcome non-response problem is to contact the non-respondent and obtain the information as much as possible. Hansen and Hurwitz (1946) were the first to deal with the problem of non-response. They proposed a sampling scheme that involves taking a subsample of non-responds after the first mail attempt and then obtain the information by personal interview.

For a finite population $U = \{U_1, U_2, ..., U_N\}$ of size N and a random sample of size n is drawn without replacement. Let the characteristics under study, say, y takes value y_i on the unit U_i ($I = 1, 2, ..., N$). In survey on human population it is often the case that n_1 unit respond on the first attempt while n_1 ($= n - n_1$) units do not provide any response. In the case of non-response of at initial stage Hansen

and Hurwitz (1946) suggested a double sampling plan for estimating the population mean comprising the following steps:

i. A simple random sample of size n is drawn and the questionnaire is mailed to the sample units;

ii. A sub-sample of size $r = (n_2 / k)$, $(k > 1)$ from the n_2 non responding units in the initial step attempt is contacted through personal interviews.

Note that Hansen and Hurwitz (1946) considered the mail surveys at the first attempt and the personal interviews at the second attempt. In the Hansen and Hurwitz method the population is supposed to be consisting of response stratum of size N_1 and the non-response stratum of size $N_2 = (N - N_1)$. Let $\bar{Y} = \sum_{i=1}^{N} y_i / N$ and $S_y^2 = \sum_{i=1}^{N} (y_i - \bar{Y})^2 / (N - 1)$ denote the mean and the population variance of the study variable y. Let $\bar{Y}_1 = \sum_{i=1}^{N_1} y_i / N_1$ and $S_{y(1)}^2 = \sum_{i=1}^{N_1} (y_i - \bar{Y})^2 / (N_1 - 1)$ denote the mean and variance of response group. Similarly, let $\bar{Y}_2 = \sum_{i=1}^{N_2} y_i / N_2$ and $S_{y(2)}^2 = \sum_{i=1}^{N_2} (y_i - \bar{Y})^2 / (N_2 - 1)$ denote the mean and variance of the non-response group. The population mean can be written as $\bar{Y} = W_1 \bar{Y}_1 + W_2 \bar{Y}_2$, where $W_1 = (N_1 / N)$ and $W_2 = (N_2 / N)$. The sample mean $\bar{y}_1 = \sum_{i=1}^{n_1} y_i / n_1$ is an unbiased for $\bar{Y}_1$, but has a bias equal to $W_2 (\bar{Y}_1 - \bar{Y}_2)$ in estimating the population mean $\bar{Y}$.

The sample mean $\bar{y}_{2r} = \sum_{i=1}^{r} y_i / r$ is unbiased for the mean y_2 for the n_2 units. Hansen and Hurwitz (1946) suggested an unbiased estimator for the population mean $\bar{Y}$ is given by $\bar{y}^* = w_1 \bar{y}_1 + w_2 \bar{y}_{2r}$.

Where $w_1 = (n_1 / n)$ and $w_2 = (n_2 / n)$ are responding and non-responding proportions in the sample. The variance of $\bar{y}^*$ is given by

$$V(\bar{y}^*) = \left(\frac{1-f}{n}\right) S_y^2 + \frac{W_2 (k-1)}{n} S_{y(2)}^2 ; \text{ where } f = (n / N).$$

In the sampling literature, it is known that efficiency of the estimator of population mean of a study variable y can be increased by the use of auxiliary information related to x which is highly correlated with study variable y. Cochran (1977) suggested the ratio and regression estimator of the population mean $\bar{Y}$ of study variable y in which information on the auxiliary variable is obtained from all sample units, and the population mean of auxiliary variable x is known, while some units do not provide any information on study variable y. Rao (1986), Khare and Srivastava (1995,1997), Okafor and Lee (2000) and Singh and Kumar (2008, 2009, 2010) have suggested some estimator for population mean of the study variable y using auxiliary information in presence of non-response.

Let x_i, $(i = 1, 2, \ldots, N)$ denote a auxiliary characteristics correlated with the study variable y_i, $(i = 1, 2, \ldots, N)$ the population mean of auxiliary variable is $\bar{X} = \sum_{i=1}^{N} x_i / N$. Let $\bar{X}_1$ and $\bar{X}_2$ denote the population means of the response and non-response groups. Let $\bar{x}_1 = \sum_{i=1}^{n_2} x_i / n_2, \bar{x}_2 = \sum_{i=1}^{n_2} x_i / n_2, \bar{x}_{2r} = \sum_{i=1}^{r} x_i / r$ denote the means of the n_1 responding units, n_2 non-responding units, and $r = (n_2 / k)$ sub-sampled units respectively. In this paper we have merged two major concepts for improvement of estimation techniques that is consideration of measurement error and non-response in the estimation procedure and proposed a class of estimators.

Notations

Let $\bar{x} = \dfrac{1}{n} \sum_{i=1}^{n} x_i, \bar{y} = \dfrac{1}{n} \sum_{i=1}^{n} y_i$, be the unbiased estimator of population means $\bar{X}$ and $\bar{Y}$, respectively but $s_x^2 = \dfrac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$ and $s_y^2 = \dfrac{1}{n-1} \sum_{i=1}^{n} (y_i - \bar{y})^2$ are not unbiased estimator of (σ_x^2, σ_y^2), respectively. The expected values of s_x^2 and s_y^2 in the presence of measurement error are, given by,

$$E\left(s_x^2\right) = \sigma_x^2 + \sigma_v^2$$

$$E\left(s_y^2\right) = \sigma_y^2 + \sigma_u^2$$

and for non-response group

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$$E\left(s_{x_2}^2\right)=\sigma_{x_2}^2+\sigma_{v_2}^2$$
$$E\left(s_{y_2}^2\right)=\sigma_{y_2}^2+\sigma_{u_2}^2.$$

When the error variance σ_v^2 is known, the unbiased estimator of σ_x^2, is $\hat{\sigma}_x^2=s_x^2-\sigma_v^2>0$, and when σ_u^2 is known, then the unbiased estimator of σ_y^2 is $\hat{\sigma}_y^2=s_y^2-\sigma_u^2>0$.

Similarly, for the non-response group the unbiased estimator of $\sigma_{x_2}^2$, is $\hat{\sigma}_{x_2}^2=s_{x_2}^2-\sigma_{v_2}^2>0$, and when $\sigma_{u_2}^2$ is known, then the unbiased estimator of $\sigma_{y_2}^2$ is $\hat{\sigma}_{y_2}^2=s_{y_2}^2-\sigma_{u_2}^2>0$.

$$E\left(s_{x_2}^2\right)=\sigma_{x_2}^2+\sigma_{v_2}^2$$
$$E\left(s_{y_2}^2\right)=\sigma_{y_2}^2+\sigma_{u_2}^2.$$

Define

$$\bar{y}=\mu_y\left(1+e_0\right)$$
$$\bar{x}=\mu_x\left(1+e_1\right)$$

such that

$$E\left(e_0\right)=E\left(e_1\right)=0,$$

and up to the first degree of approximation (when finite population correction factor is ignored)

$$E\left(e_0^2\right) = \frac{C_y^2}{n}\left(1+\frac{S_u^2}{S_y^2}\right) + \frac{W_2\left(k-1\right)}{n}C_{y_2}^2\left(1+\frac{S_{u_2}^2}{S_{y_2}^2}\right)$$

$$E\left(e_1^2\right) = \frac{C_x^2}{n}\left(1+\frac{S_v^2}{S_x^2}\right) + \frac{W_2\left(k-1\right)}{n}C_{x_2}^2\left(1+\frac{S_{v_2}^2}{S_{x_2}^2}\right)$$

$$E\left(e_0 e_1\right) = \frac{\rho_{yx}C_y C_x}{n} + \frac{W_2\left(k-1\right)}{n}\rho_{yx_2}C_{y_2}C_{x_2}$$

$$C_y = S_y/\bar{Y}, C_x = S_x/\bar{X}, C_{y_2} = S_{y_2}/\bar{Y}, C_{x_2} = S_{x_2}/\bar{X}, \rho_{xy} = S_{xy}/S_x S_y$$

Adapted estimator

A traditional estimator for estimating population mean in the simultaneous presence of response and non-response error is given by,

$$t_1 = \bar{y} \tag{3}$$

Expression (3) can be written as

$$t_1 - \bar{Y} = \bar{Y}^2\left(1+e_0\right) \tag{4}$$

Taking expectation both sides of (4), we get bias of estimator t_1 given as

$$Bias\left(t_1\right) = 0 \tag{5}$$

Squaring both sides of (4)

$$\left(t_1 - \bar{Y}\right)^2 = \bar{Y}^2 e_0^2 \tag{6}$$

and taking expectation and using notation, mean square error of t_1 is obtained up to first order of approximation, as

$$MSE\left(t_1\right) = \frac{S_y^2}{n}\left(1+\frac{\sigma_u^2}{S_y^2}\right) + AS_{y2}^2\left(1+\frac{\sigma_{u2}^2}{S_{y2}^2}\right) \tag{7}$$

or

$$MSE(t_1) = M \tag{8}$$

where, $A = \dfrac{(k-1)W_2}{n}$ and $M = \dfrac{S_y^2}{n}\left(1 + \dfrac{\sigma_u^2}{S_y^2}\right) + AS_{y2}^2\left(1 + \dfrac{\sigma_{u2}^2}{S_{y2}^2}\right)$.

In the case, when the measurement error is zero or negligible, MSE of estimator t_1 is given by,

$$MSE^*(t_1) = \dfrac{S_y^2}{n} + AS_{y2}^2 \tag{9}$$

where, $M_{t_1} = \dfrac{\sigma_u^2}{n} + A\sigma_{u2}^2$ is the contribution of measurement errors in t_1.

When there is non-response and response error both are present, a ratio type estimator for estimating population mean is, given by

$$t_r = \dfrac{\bar{y}^*}{\bar{x}^*}\bar{X} \tag{10}$$

Expressing the estimator t_r in terms of e's

$$t_r = \bar{Y}(1+e_0)(1+e_1)^{-1} \tag{11}$$

Expanding equation (11) and simplifying,

$$(t_r - \bar{Y}) = \bar{Y}\left[e_0 - e_1 - e_0e_1 + e_1^2\right] \tag{12}$$

and taking expectation both sides of (12), the bias of estimator t_r is

$$Bias(t_r) = \left[\dfrac{S_x^2}{n}\left(1 + \dfrac{\sigma_v^2}{S_x^2}\right) + AS_{x2}^2\left(1 + \dfrac{\sigma_{v2}^2}{S_{x2}^2}\right) - 2\left(\dfrac{1}{n}\rho_{xy}S_xS_y + A\rho_{xy2}S_{x2}S_{y2}\right)\right] \tag{13}$$

Squaring both sides of (12),

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$$\left(t_r - \sigma_y^2\right)^2 = \bar{Y}^2 \left[e_0^2 + e_1^2 - 2e_0 e_1\right] \tag{14}$$

Taking expectations of (14) and using notations, we get the MSE of estimator t_r as

$$MSE(t_r) = \frac{1}{n}\left[S_y^2\left(1 + \frac{\sigma_u^2}{S_y^2}\right) + S_x^2\left(1 + \frac{\sigma_v^2}{S_x^2}\right) - 2\rho_{xy}S_x S_y\right]$$
$$+ A\left[S_{y2}^2\left(1 + \frac{\sigma_{u2}^2}{S_{y2}^2}\right) + S_{x2}^2\left(1 + \frac{\sigma_{v2}^2}{S_{x2}^2}\right) - 2\rho_{xy2}S_{x2}S_{y2}\right] \tag{15}$$

$$= \left[\begin{array}{c} \dfrac{S_y^2}{n}\left(1 + \dfrac{\sigma_u^2}{S_y^2}\right) + AS_{y2}^2\left(1 + \dfrac{\sigma_{u2}^2}{S_{y2}^2}\right) + \dfrac{S_x^2}{n}\left(1 + \dfrac{\sigma_v^2}{S_x^2}\right) \\[3mm] + AS_{x2}^2\left(1 + \dfrac{\sigma_{v2}^2}{S_{x2}^2}\right) - 2\left(\dfrac{1}{n}\rho_{xy}S_x S_y + A\rho_{xy2}S_{x2}S_{y2}\right) \end{array}\right] \tag{16}$$

$$= M + N - 2O$$

where,

$$M = \left\{\frac{1}{n}S_y^2\left(1 + \frac{\sigma_u^2}{S_y^2}\right) + AS_{y2}^2\left(1 + \frac{\sigma_{u2}^2}{S_{y2}^2}\right)\right\}$$

$$N = \left\{\frac{1}{n}S_x^2\left(1 + \frac{\sigma_v^2}{S_x^2}\right) + AS_{x2}^2\left(1 + \frac{\sigma_{v2}^2}{S_{x2}^2}\right)\right\}$$

$$O = \left\{\frac{1}{n}\rho_{xy}S_x S_y + A\rho_{xy2}S_{x2}S_{y2}\right\}.$$

A regression estimator under measurement error and non-response is defined as

$$t_{lr} = \bar{y}^* + b\left(\bar{X} - \bar{x}^*\right) \tag{17}$$

Expressing the estimator t_r in terms of e's, $t_{lr} = \bar{Y}\left(1 + e_0\right) - b\bar{X}e_1$,

and expanding equation (17) and simplifying,

$$\left(t_{lr} - \bar{Y}\right) = \left(\bar{Y}e_0 - b\bar{X}e_1\right) \tag{18}$$

Squaring both sides of (18) and after simplification,

$$\left(t_{lr} - \bar{Y}\right)^2 = \left[\bar{Y}^2 e_0^2 + b^2 \bar{X}^2 e_1^2 - 2b\bar{X}\bar{Y}e_0 e_1\right] \tag{19}$$

Taking expectations both sides of (19) the MSE of estimator t_{lr} is obtained as

$$MSE\left(t_{lr}\right) = M + b^2 R^2 N - 2bRO \tag{20}$$

The optimum value of b is obtained by minimizing (20) and is given by

$$b^* = \frac{1}{R}\left[\frac{O}{N}\right] \tag{21}$$

Substituting the optimal value of b in equation (20), the minimum MSE of the estimator t_{lr} is obtained as

$$MSE\left(t_{lr}\right)_{\min} = M\left[1 - \frac{O^2}{MN}\right] \tag{22}$$

In the case, when the measurement error is zero or negligible, MSE of estimator t_1 is given by

$$MSE\left(t_{lr}\right) = \frac{1}{n}S_y^2\left[1 - \rho_{xy}^2\right] + \frac{(k-1)W_2}{n}\left[S_{y2}^2 + b^2 S_{x2}^2 - 2b\rho_{xy2}S_{x2}S_{y2}\right] \tag{23}$$

Proposed class of estimator

A proposed class of estimators given by

$$t_p = m_1 \bar{y}^* + m_2 \frac{\bar{y}^*}{\bar{x}^*}\bar{X} \tag{24}$$

Note for $(m_1, m_2) = (1, 0)$ $t_1 = \overline{y}^*$ (usual unbiased estimator), and for $(m_1, m_2) = (0, 1)$ $t_2 = \dfrac{\overline{y}^*}{\overline{x}^*} \overline{X}$ (usual ratio estimator). Thus, the proposed class of estimators is generalized version of usual unbiased estimator and ratio estimator. Expressing the estimator t_p in terms of e's

$$t_p = m_1 \overline{Y}\left(1 + e_0\right) + m_2 \overline{Y}\left(1 + e_0\right)\left(1 + e_1\right)^{-1} \tag{25}$$

Expanding equation (25) and simplifying,

$$\left(t_p - \overline{Y}\right) = \overline{Y}\left[e_0 + m_2\left(-e_1 + e_1^2 - e_0 e_1\right)\right] \tag{26}$$

 Squaring both sides of (26) and after simplification,

$$\left(t_p - \overline{Y}\right)^2 = \overline{Y}^2\left[e_0^2 + m_2^2 e_1^2 - 2m_2 e_0 e_1\right] \tag{27}$$

Taking expectations of (27) and using notations, the MSE of estimator t_r is obtained as

$$MSE\left(t_p\right) = M + m_2 R^2 N - 2m_2 RO \tag{28}$$

The optimum value of m_2 is obtained by minimizing (28), given by

$$m_2^* = \frac{1}{R}\left[\frac{O}{N}\right] \tag{29}$$

and $m_1^* = 1 - m_2^*$.

Substituting the optimal value of m_2 in equation (28) the minimum MSE of the estimator t_p is obtained as

$$MSE\left(t_p\right)_{\min} = M\left[1 - \frac{O^2}{MN}\right] \tag{30}$$

The minimum MSE of proposed class of estimator t_p given in (30) is same as the MSE of regression estimator under simultaneous presence of non-response and measurement error, given in equation (22).

Efficiency comparisons

First, the efficiency of the proposed estimator t_p is compared with usual unbiased estimator,

$$MSE(t_1) - MSE(t_P)_{\min} > 0$$

$$\text{If } \left[M - M\left(1 - \frac{O^2}{MN} \right) \right] > 0, \left[\frac{O^2}{MN} \right] > 0 \tag{31}$$

The condition listed in (31) shows that proposed family of estimators is always better than the usual estimator under the non-response and measurement error.

Next, the ratio estimator is compared with proposed family of estimators t_p,

$$MSE(t_2)_{\min} - MSE(t_P)_{\min} > 0, \left[(M + N - 2O) - M\left(1 - \frac{O^2}{MN} \right) \right] > 0 \tag{32}$$

$$[N - O]^2 > 0$$

Observe that the condition (32) holds and shows proposed family of estimators is better than the ratio estimator under the non-response and measurement error.

Empirical study

Data statistics

The data used for empirical study was taken from Gujarati and Sangeetha (2007, pg, 539) where,

Y_i = True consumption expenditure,

X_i = True income,

y_i = Measured consumption expenditure,

x_i = Measured income.

From the data given we get the following parameter values:

Table 1. Value of the parameters

n	μ_y	μ_x	S_y	S_x	ρ	σ_u^2	σ_v^2
70	981.29	1755.53	613.66	1406.13	0.778	36.00	36.00
μ_{y2}	μ_{x2}	S_{y2}	S_{x2}	ρ_2	R	W_2	
597.29	1100.24	244.11	631.51	0.445	0.5589	0.25	

Table 2. Showing the MSE of the estimators with and without measurement errors

Estimators	MSE Without Error	Contribution of meas. error in MSE	Contribution of non-response	MSE including me. Errors & non-response
$t_1 = \overline{y}^*$	10759.39	1.03	2553.840	13313.58
t_r	6967.135	1.35	4607.335	11574.92
t_{lr}	4246.903	0.86	2527.751	6775.036
t_p	4246.903	0.86	2527.751	6775.036

Table 2 exhibits that measurement error and non-response plays an important role in increasing the MSE of an estimator. We also conclude that contribution of measurement error and non-response in usual estimator is less than in comparison to the ratio estimator; these observations have interesting implication where the ratio estimator performs better than sample mean under the absence of any measurement error in X characteristics. There may be a case when ratio estimator is poor than sample mean under the consideration of any measurement error. It is observed from Table 2 that the performance of our proposed estimator t_p is better than usual estimator t_1 and ratio estimator t_r under non-response and measurement error. Further it is observed that contribution of non-response error is larger than the response error in increasing the MSE of the estimators.

Conclusion

A class of estimator of the population mean of study variable *y* was proposed using auxiliary information. The estimators use auxiliary information to improve efficiencies, assuming non-response and measurement error are present in both the study and auxiliary variables. In addition, some known estimator of population mean such as usual unbiased estimator and ratio estimator for population mean are found to be members of the proposed class of estimators. The MSEs of the proposed class of estimators were obtained up to the first order of approximation in the simultaneous presence of non-response and response error. The proposed class of estimators are advantageous in the sense that the properties of the estimators which are members of the proposed class of estimators can be easily obtained from the properties of the proposed class of estimators.

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