# Some Ratio-cum-product Type Estimators for Population Mean Under Double Sampling in the Presence of Non-response 

Hemant K. Verma, Prayas Sharma and Rajesh Singh*<br>Department of Statistics, Banaras Hindu University Varanasi-221005, India

Received: 31 Mar. 2014, Revised: 27 Oct. 2014, Accepted: 30 Oct. 2014
Published online: 1 Nov. 2014


#### Abstract

In this paper, we have proposed some ratio-cum-product type estimators for population mean of the study variable $y$ in the presence of non-response using auxiliary information under double sampling. The expressions of mean squared error (MSE) of the proposed estimators are derived under double (two-stage) sampling. In addition, an empirical study is carried out to show the properties of the proposed estimators..


Keywords: Auxiliary variable, double sampling, mean Square error, efficiency.

## 1 Introduction

In surveys covering socio-economic studies, several variables are considered simultaneously. While conducting a households survey for the study of several variables information is in most of the cases, not obtained from all the units in the survey even after some call backs. An estimate obtained from such incomplete data is misleading, especially when the respondents differ from non-respondents because the estimate can be biased (see [7] ). [3] suggested a technique for sub-sampling the non-respondents in order to adjust for non-response in mail surveys. In estimating population parameters use of auxiliary information improves precision of an estimate when auxiliary variable x is highly correlated with the study variable y (see [15,14]). Several authors including [2], [9,10], [4,5] and [16,17] discussed the problem of estimating the population mean $\bar{Y}$ of study variable y when the population mean $\bar{X}$ of auxiliary variable x is known in the presence of non response. Also some other authors including [11], [13] have discussed the problem of estimating the population mean under double sampling with non- response.

Let y be the study variable and $x_{1}, x_{2}$ be the auxiliary variables. Let $\bar{Y}, \bar{X}_{1}$ and $\bar{X}_{2}$ are the population means of study and auxiliary variables, respectively. Here, we assume that $\bar{X}_{2}$ is known and $\bar{X}_{1}$ is unknown. By using simple random sampling without replacement (SRSWOR), we draw a preliminary sample of size $n^{\prime}$ from the population of size N and on the basis of $n^{\prime}$ units we estimate the unknown population mean $\overline{X_{1}}$ as $\overline{x_{1}}{ }^{\prime}$.

Now, we draw a subsample of size n from the preliminary sample of size $n^{\prime}$ using SRSWOR and we observe that $n_{1}$ units respond and $n_{2}$ units do not respond in the sample of size $n$ for the study variable $y$. Using [3] technique of sub sampling, a sub sample of r units is selected from the $n_{2}$ non respondent units and enumerate completely by direct interview, such that $r=\left(n_{2} / L\right), L>1$, where L is the inverse sampling rate. Here we assume that response is obtained for all the r units. Thus we have $\left(n_{1}+r\right)$ observation on study variable y . Using [3] technique, the estimator for population mean using $\left(n_{1}+r\right)$ observations on study variable y is given by

$$
\begin{equation*}
\bar{y}^{*}=\frac{n_{1} \bar{y}_{1}+n_{2} \bar{y}_{r 2}}{n} \tag{1}
\end{equation*}
$$

[^0]where $\bar{y}_{1}$ and $\bar{y}_{r 2}$ denote the sample means of y based on $n_{1}$ and $r$ units respectively.
The estimator $\bar{y}^{*}$ is unbiased and has variance
\[

$$
\begin{equation*}
V\left(\bar{y}^{*}\right)=\frac{1-f}{n} S_{y}^{2}+\frac{L-1}{n} K S_{y_{2}}^{2} \tag{2}
\end{equation*}
$$

\]

where, $f=\frac{n}{N}, K=\frac{N_{2}}{N}, S_{y}^{2}$ and $S_{y 2}^{2}$ are the population mean squares of y for the entire population and for the nonresponding part of the population, respectively.
[6] proposed a ratio type estimator of population mean using available information on two auxiliary variables in the presence of non response, given by

$$
\begin{equation*}
\bar{y}_{R}=\bar{y}^{*}\left(\frac{\bar{x}_{1}^{\prime}}{\bar{x}_{1}}\right)\left(\frac{\bar{x}_{2}}{\bar{x}_{2}^{\prime}}\right) \tag{3}
\end{equation*}
$$

The mean square error (MSE) expression of (3) is given by

$$
\begin{equation*}
\operatorname{MSE}\left(\bar{y}_{R}\right)=\bar{Y}^{2}\left[f_{1} C_{y}^{2}+\left(f_{1}-f_{2}\right) C_{x_{1}}^{2}+f_{2} C_{x_{2}}^{2}-2\left(f_{1}-f_{2}\right) \rho_{y x_{1}} C_{y} C_{x_{1}}-\rho_{y x_{2}} C_{y} C_{x_{2}}\right]+\frac{L-1}{n} K S_{y 2}^{2} \tag{4}
\end{equation*}
$$

[12] ratio-cum-product estimator of population mean in double sampling under non-response using two auxiliary variables, is given by

$$
\begin{equation*}
\bar{y}_{r p d}=\bar{y}^{*}\left(\frac{\bar{x}_{1}^{\prime}}{\bar{x}_{1}}\right)^{\alpha_{1}}\left(\frac{\bar{x}_{2}^{\prime}}{\bar{X}_{2}}\right)^{\alpha_{2}} \tag{5}
\end{equation*}
$$

where $\alpha_{1}$ and $\alpha_{2}$ are constants.
The MSE expression of (5) is given as

$$
\begin{equation*}
\operatorname{MSE}\left(\bar{y}_{r p d}\right)=\bar{Y}^{2}\left[f_{1} C_{y}^{2}\left(1-\rho_{y x_{1}}^{2}\right)+f_{2} C_{y}^{2}\left(\rho_{y x_{1}}^{2}-\rho_{y x_{2}}^{2}\right)\right]+\frac{L-1}{n} K S_{y_{2}}^{2} \tag{6}
\end{equation*}
$$

In this paper, motivated by [8] ratio-cum-product type estimator is presented in the presence of non-response under double sampling scheme. The expressions for the bias and mean square error of the proposed estimator are obtained and compared with relevant estimators. The expression of minimum variance has been obtained for the optimum value of $n$, $n^{\prime}$ and $L$ for fixed $\operatorname{cost} C \leq C_{0}$ and for the specified variance $V=V_{0}^{\prime}$.

## 2 Proposed Estimator

Motivated by [8], we have proposed some ratio-cum-product type estimators under double sampling, defined as

$$
\begin{align*}
& T_{1}=\bar{y}^{*}\left\{\frac{\bar{x}_{2}^{\prime}+\alpha_{21}\left(\bar{x}_{2}-\bar{x}_{2}^{\prime}\right)}{\bar{x}_{1}+\alpha_{11}\left(\bar{x}_{1}^{\prime}-\bar{x}_{1}\right)}\right\}\left\{\frac{\bar{x}_{1}^{\prime}}{\bar{x}_{2}}\right\}  \tag{7}\\
& T_{2}=\bar{y}^{*}\left\{\frac{\bar{x}_{1}^{\prime}}{\bar{x}_{1}+\alpha_{12}\left(\bar{x}_{1}^{\prime}-\bar{x}_{1}\right)}\right\}\left\{\frac{\bar{x}_{2}}{\bar{x}_{2}^{\prime}+\alpha_{22}\left(\bar{x}_{2}-\bar{x}_{2}^{\prime}\right)}\right\}  \tag{8}\\
& T_{3}=\bar{y}^{*}\left\{\frac{\bar{x}_{1}+\alpha_{13}\left(\bar{x}_{1}^{\prime}-\bar{x}_{1}\right)}{\bar{x}_{1}^{\prime}}\right\}\left\{\frac{\bar{x}_{2}^{\prime}+\alpha_{23}\left(\bar{X}_{2}-\bar{x}_{2}^{\prime}\right)}{\bar{X}_{2}}\right\}  \tag{9}\\
& T_{4}=\bar{y}^{*}\left\{\frac{\bar{x}_{1}+\alpha_{14}\left(\bar{x}_{1}^{\prime}-\bar{x}_{1}\right)}{\bar{x}_{2}^{\prime}+\alpha_{24}\left(\bar{X}_{2}-\bar{x}_{2}^{\prime}\right)}\right\}\left\{\frac{\bar{x}_{2}}{\bar{x}_{1}^{\prime}}\right\} \tag{10}
\end{align*}
$$

To obtain the bias and MSE expressions of the estimators $T_{i}(i=1,2,3,4)$ to the first degree of approximation, we define $e_{0}=\frac{\bar{y}^{*}-\bar{Y}}{\bar{Y}}, e_{1}=\frac{\bar{x}_{1}-\bar{X}_{1}}{\bar{X}_{1}}, e_{1}^{\prime}=\frac{\bar{x}_{1}^{\prime}-\bar{X}_{1}}{\bar{X}_{1}}, e_{2}^{\prime}=\frac{\bar{x}_{2}^{\prime}-\bar{X}_{2}}{\bar{X}_{2}}$
such that, $E\left(e_{0}\right)=E\left(e_{1}\right)=E\left(e_{1}^{\prime}\right)=E\left(e_{2}^{\prime}\right)=0$
Also, $E\left(e_{0}^{2}\right)=f_{1} C_{y}^{2}+\frac{L-1}{n} K C_{y_{2}}^{2}, E\left(e_{1}^{2}\right)=f_{1} C_{x_{1}}^{2}, E\left(e_{1}^{\prime 2}\right)=f_{2} C_{x_{1}}^{2}, E\left(e_{2}^{\prime 2}\right)=f_{2} C_{x_{2}}^{2}$,
$E\left(e_{0} e_{1}\right)=f_{1} \rho_{y x_{1}} C_{y} C_{x_{1}}, E\left(e_{0} e_{1}^{\prime}\right)=f_{2} \rho_{y x_{1}} C_{y} C_{x_{1}}, E\left(e_{0} e_{2}^{\prime}\right)=f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}, E\left(e_{1} e_{1}^{\prime}\right)=f_{2} C_{x_{1}}^{2}$,
$E\left(e_{1} e_{2}^{\prime}\right)=f_{2} \rho_{x_{1} x_{2}} C_{x_{1}} C_{x_{2}}, E\left(e_{1}^{\prime} e_{2}^{\prime}\right)=f_{2} \rho_{x_{1} x_{2}} C_{x_{1}} C_{x_{2}}$
$C_{y}=\frac{S_{y}}{\bar{Y}}, C_{x_{1}}=\frac{S_{x_{1}}}{\bar{X}_{1}}, C_{x_{2}}=\frac{S_{x_{2}}}{\bar{X}_{2}}, C_{y_{2}}=\frac{S_{y_{2}}}{\bar{Y}}, f_{1}=\frac{1}{n}-\frac{1}{N}, f_{2}=\frac{1}{n^{\prime}}-\frac{1}{N}$
$S_{y}^{2}=\frac{1}{N-1} \sum_{i=1}^{N}\left(Y_{i}-\bar{Y}\right)^{2}, S_{x_{1}}^{2}=\frac{1}{N-1} \sum_{i=1}^{N}\left(X_{1 i}-\bar{X}_{1}\right)^{2}, S_{x_{2}}^{2}=\frac{1}{N-1} \sum_{i=1}^{N}\left(X_{2 i}-\bar{X}_{2}\right)^{2}, S_{y_{2}}^{2}=\frac{1}{N_{2}-1} \sum_{i=1}^{N_{2}}\left(Y_{2 i}-\bar{Y}_{2}\right)^{2}$
Expressing (7) in terms of e's, we have

$$
\begin{align*}
& T_{1}=\bar{Y}\left(1+e_{0}\right)\left\{\frac{\bar{X}_{2}\left(1+e_{2}^{\prime}\right)+\alpha_{21}\left(\bar{X}_{2}-\bar{X}_{2}\left(1+e_{2}^{\prime}\right)\right)}{\bar{X}_{1}\left(1+e_{1}\right)+\alpha_{11}\left(\bar{X}_{1}\left(1+e_{1}^{\prime}\right)-\bar{X}_{1}\left(1+e_{1}\right)\right)}\right\}\left\{\frac{\bar{X}_{1}\left(1+e_{1}^{\prime}\right)}{\bar{X}_{2}}\right\} \\
& T_{1}=\bar{Y}\left(1+e_{0}\right)\left(1+e_{1}^{\prime}\right)\left(1+\left(1-\alpha_{21}\right) e_{2}^{\prime}\right)\left(1+e_{1}+\alpha_{11}\left(e_{1}^{\prime}-e_{1}\right)\right)^{-1} \tag{11}
\end{align*}
$$

Expanding the right hand side of (11) and retaining terms up to second degrees of e's, we have

$$
\begin{align*}
T_{1} & =\bar{Y}\left[1+\left(1-\alpha_{11}\right)^{2} e_{1}^{2}-\left(1-\alpha_{11}\right)\left\{e_{1}+e_{0} e_{1}+e_{1} e_{1}^{\prime}\right\}+\left(1-\alpha_{21}\right)\left\{e_{2}^{\prime}+e_{1}^{\prime} e_{2}^{\prime}+e_{0} e-2^{\prime}\right\}-\alpha_{11}\left\{e_{1}^{\prime}+e_{1}^{\prime 2}+e_{0} e_{1}^{\prime}\right\}\right. \\
& \left.+\alpha_{11}^{2} e_{1}^{\prime 2}+2 \alpha_{11}\left(1-\alpha_{11}\right) e_{1} e_{1}^{\prime}-\alpha_{11}\left(1-\alpha_{21}\right) e_{1}^{\prime} e_{2}^{\prime}+e_{1}^{\prime}+e_{0} e_{1}^{\prime}+e_{0}\right] \tag{12}
\end{align*}
$$

Taking expectations of both sides of (12) and then subtracting $\bar{Y}$ from both sides, we get the bias of the estimator $T_{1}$ up to the first order of approximation as

$$
\begin{align*}
\operatorname{Bias}\left(T_{1}\right) & =\bar{Y}\left[\left(1-\alpha_{11}\right)^{2} f_{1} C_{x_{1}}^{2}-\left(1-\alpha_{11}\right) \rho_{y x_{1}} C_{y} C_{x-1}\left(f_{1}+f_{2}\right)+\left(1-\alpha_{21}\right) f_{2} C_{x_{2}}\left\{\rho_{x_{1} x_{2}} C_{x_{1}}+\rho_{y x_{2}} C_{y}\right\}\right. \\
& -\alpha_{11} f_{2} C_{x_{1}}\left\{C_{x_{1}}+\rho_{y x_{1}} C_{y}\right\}+\alpha_{11}^{2} f_{2} C_{x_{1}}^{2}+2 \alpha_{11}\left(1-\alpha_{11}\right) f_{2} C_{x_{1}}^{2}-\alpha_{11}\left(1-\alpha_{21}\right) f_{2} \rho_{x_{1} x_{2}} C_{x_{1}} C_{x_{2}} \\
& \left.+f_{2} \rho_{y x_{1}} C_{y} C_{x_{1}}\right] \tag{13}
\end{align*}
$$

From (12), we have

$$
\begin{equation*}
\left(T_{1}-\bar{Y}\right) \cong \bar{Y}\left[e_{0}+\left(1-\alpha_{11}\right) e_{1}^{\prime}-\left(1-\alpha_{11}\right) e_{1}+\left(1-\alpha_{21}\right) e_{2}^{\prime}\right] \tag{14}
\end{equation*}
$$

Squaring both sides of (14) and then taking expectations, we get the MSE of $T_{1}$ up to the first order of approximation as

$$
\begin{align*}
\operatorname{MSE}\left(T_{1}\right) & =\bar{Y}^{2}\left[f_{1} C_{y}^{2}+\left(1-\alpha_{11}\right)^{2} C_{x_{1}}^{2}\left(f_{1}-f_{2}\right)+\left(1-\alpha_{21}\right)^{2} f_{2} C_{x_{2}}^{2}-2\left(1-\alpha_{11}\right) \rho_{y x_{1}} C_{y} C_{x_{1}}\left(f_{1}-f_{2}\right)\right. \\
& \left.+2\left(1-\alpha_{21}\right) f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}\right]+\frac{L-1}{n} K S_{y_{2}}^{2} \tag{15}
\end{align*}
$$

Partially differentiating (15) with respect to $\alpha_{11}$ and $\alpha_{21}$ and equating to zero, we get the optimum values of $\alpha_{11}$ and $\alpha_{21}$ , as

$$
\alpha_{11(o p t)}=1-\rho_{y x_{1}} \frac{C_{y}}{C_{x_{1}}} \quad \text { and } \quad \alpha_{21(o p t)}=1+\rho_{y x_{2}} \frac{C_{y}}{C_{x_{2}}}
$$

Similarly, we get the bias and MSE expressions of the estimators $T_{2}, T_{3}$ and $T_{4}$ respectively, as

$$
\begin{align*}
\operatorname{Bias}\left(T_{2}\right) & =\bar{Y}\left[\left(1-\alpha_{12}\right)^{2} f_{1} C_{x_{1}}^{2}+\left(1-\alpha_{22}\right)^{2} f_{2} C_{x_{2}}^{2}+\left(1-\alpha_{12}\right)\left(1-\alpha_{22}\right) f_{2} \rho_{x_{1} x_{2}} C_{x_{1}} C_{x_{2}}\right. \\
& +\alpha_{12}\left(1-\alpha_{12}\right) f_{2}\left\{C_{x_{1}}^{2}+\rho_{x_{1} x_{2}} C_{x_{1}} C_{x_{2}}+\rho_{y x_{1}} C_{y} C_{x_{1}}\right\}-\left(1-\alpha_{12}\right)\left\{f_{2} C_{x_{1}}^{2}+f_{1} \rho_{y x_{1}} C_{y} C_{x_{1}}\right\} \\
& \left.-\left(1-\alpha_{22}\right) f_{2} C_{x_{2}}\left\{\rho_{x_{1} x_{2}} C_{x_{1}} C_{x_{2}}+\rho_{y x_{2}} C_{y} C_{x_{2}}\right\}-\alpha_{12} f_{2} C_{x_{1}}\left\{C_{x_{1}} \rho_{y x_{1}} C_{y}\right\}+f_{2} \rho_{y x_{1}} C_{y} C_{x_{1}}\right] \tag{16}
\end{align*}
$$

$$
\begin{align*}
\operatorname{Bias}\left(T_{3}\right) & =\bar{Y}\left[f_{2}\left\{C_{x_{2}}^{2}-\rho_{y x_{1}} C_{y} C_{x_{1}}\right\}+\left(1-\alpha_{23}\right) f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}+\left(1-\alpha_{13}\right) C_{x_{1}}\left\{f_{1} \rho_{y x_{1}} C_{y}-f_{2} C_{x_{1}}\right\}\right. \\
& \left.+\alpha_{13} f_{2} C_{x_{1}}\left\{\rho_{y x_{1}} C_{y}-C_{x_{1}}\right\}\right] \tag{17}
\end{align*}
$$

$$
\begin{align*}
\operatorname{Bias}\left(T_{4}\right) & =\bar{Y}\left[f_{2} C_{x_{2}}^{2}+\left(1-\alpha_{24}\right) f_{2} C_{x_{2}}^{2}-f_{2} \rho_{y x_{1}} C_{y} C_{x_{1}}-\left(1-\alpha_{14}\right) C_{x_{1}}\left\{f_{1} \rho_{y x_{1}} C_{y}-f_{2} C_{x_{1}}\right\}\right. \\
& \left.-\left(1-\alpha_{24}\right) f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}+\alpha_{14} f_{2} C_{x_{1}}\left\{\rho_{y x_{1}} C_{y}-C_{x_{1}}\right\}\right] \tag{18}
\end{align*}
$$

and

$$
\begin{align*}
\operatorname{MSE}\left(T_{2}\right) & =\bar{Y}^{2}\left[f_{1} C_{y}^{2}+\left(1-\alpha_{12}\right)^{2} C_{x_{1}}^{2}\left(f_{1}-f_{2}\right)+\left(1-\alpha_{22}\right)^{2} f_{2} C_{x_{2}}^{2}-2\left(1-\alpha_{12}\right) \rho_{y x_{1}} C_{y} C_{x_{1}}\left(f_{1}-f_{2}\right)\right. \\
& \left.-2\left(1-\alpha_{22}\right) f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}\right]+\frac{L-1}{n} K S_{y_{2}}^{2} \tag{19}
\end{align*}
$$

where

$$
\alpha_{12(o p t)}=1-\rho_{y x_{1}} \frac{C_{y}}{C_{x_{1}}} \quad \text { and } \quad \alpha_{22(o p t)}=1-\rho_{y x_{2}} \frac{C_{y}}{C_{x_{2}}}
$$

$$
\begin{align*}
\operatorname{MSE}\left(T_{3}\right) & =\bar{Y}^{2}\left[f_{1} C_{y}^{2}+\left(1-\alpha_{13}\right)^{2} C_{x_{1}}^{2}\left(f_{1}-f_{2}\right)+\left(1-\alpha_{23}\right)^{2} f_{2} C_{x_{2}}^{2}-2\left(1-\alpha_{13}\right) \rho_{y x_{1}} C_{y} C_{x_{1}}\left(f_{1}-f_{2}\right)\right. \\
& \left.+2\left(1-\alpha_{23}\right) f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}\right]+\frac{L-1}{n} K S_{y_{2}}^{2} \tag{20}
\end{align*}
$$

where

$$
\begin{gather*}
\alpha_{13(o p t)}=1-\rho_{y x_{1}} \frac{C_{y}}{C_{x_{1}}} \text { and } \alpha_{23(o p t)}=1+\rho_{y x_{2}} \frac{C_{y}}{C_{x_{2}}} \\
\operatorname{MSE}\left(T_{4}\right)=\bar{Y}^{2}\left[f_{1} C_{y}^{2}+\left(1-\alpha_{14}\right)^{2} C_{x_{1}}^{2}\left(f_{1}-f_{2}\right)+\left(1-\alpha_{24}\right)^{2} f_{2} C_{x_{2}}^{2}+2\left(1-\alpha_{14}\right) \rho_{y x_{1}} C_{y} C_{x_{1}}\left(f_{1}-f_{2}\right)\right. \\
\left.-2\left(1-\alpha_{24}\right) f_{2} \rho_{y x_{2}} C_{y} C_{x_{2}}\right]+\frac{L-1}{n} K S_{y_{2}}^{2} \tag{21}
\end{gather*}
$$

where

$$
\alpha_{14(o p t)}=1+\rho_{y x_{1}} \frac{C_{y}}{C_{x_{1}}} \quad \text { and } \quad \alpha_{24(o p t)}=1-\rho_{y x_{2}} \frac{C_{y}}{C_{x_{2}}}
$$

## 3 Determination of $n^{\prime}, n$ and $L$ (for the fixed cost $C \leq C_{0}$ )

Let $C_{0}$ be the total cost (fixed) of the survey apart from overhead cost. The expected total cost of the survey apart from overhead cost is given by

$$
\begin{equation*}
C^{\prime}=\left(c_{1}^{\prime}+c_{2}^{\prime}\right) n^{\prime}+c_{1} n+c_{2} n_{1}+c_{3} \frac{n_{2}}{L} \tag{22}
\end{equation*}
$$

Since $C^{\prime}$ vary from sample to sample, so the expected cost can be written as:

$$
\begin{equation*}
C=E\left(C^{\prime}\right)=\left(c_{1}^{\prime}+c_{2}^{\prime}\right) n^{\prime}+n\left(c_{1}+c_{2} w_{1}+c_{3} \frac{w_{2}}{L}\right) \tag{23}
\end{equation*}
$$

where
$c_{1}^{\prime}$ is the cost per unit of obtaining information on auxiliary variable $x_{1}$.
$c_{2}^{\prime}$ is the cost per unit of obtaining information on additional auxiliary variable $x_{2}$.
$c_{1}$ is the cost per unit of mailing questionnaire/visiting the unit at the subsample.
$c_{2}$ is the cost per unit of collecting, processing data obtained from $n_{1}$ responding units.
$c_{3}$ is the cost per unit of obtaining and processing data (after extra efforts) for the sub sampling units.
and $w_{1}=\frac{N_{1}}{N}, w_{2}=\frac{N_{2}}{N}$, response rate and non-response rate in the population.
The expression $\operatorname{Var}\left(T_{i}\right), i=1,2,3,4$ given by (15), (19), (20), (21), can be written as

$$
\begin{equation*}
\operatorname{Var}\left(T_{i}\right)=\left\{\frac{1}{n} V_{0 i}+\frac{1}{n^{\prime}} V_{1 i}+\frac{L}{n} V_{2 i}\right\}+\left(\text { terms inde pendent of } n, n^{\prime} \text { and } L\right) \tag{24}
\end{equation*}
$$

where $V_{0 i}, V_{1 i}$ and $V_{2 i}$ are the coefficients of the terms $\frac{1}{n}, \frac{1}{n^{\prime}}$ and $\frac{L}{n}$ in the expression for $T_{i}, i=1,2,3,4$.
Let us define a function $\phi$ as

$$
\begin{equation*}
\phi=\operatorname{Var}\left(T_{i}\right)+\lambda_{i}\left\{\left(c_{1}^{\prime}+c_{2}^{\prime}\right) n^{\prime}+n\left(c_{1}+c_{2} w_{1}+c_{3} \frac{w_{2}}{L}\right)\right\} \tag{25}
\end{equation*}
$$

where $\lambda_{i}$ is the Lagrange's multiplier.
Partially differentiating equation (25) with respect to $n^{\prime}, n$ and $L$ and equating to zero, we get,

$$
\begin{equation*}
n^{\prime}=\sqrt{\frac{V_{1 i}}{\lambda_{i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}}, n=\sqrt{\frac{\left(V_{0 i}+L V_{2 i}\right)}{\lambda_{i}\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L}\right)}} \text { and } L_{o p t}=\sqrt{\frac{V_{0 i} w_{2} c_{3}}{V_{2 i}\left(c_{1}+c_{2} w_{1}\right)}} \tag{26}
\end{equation*}
$$

Putting the value of $n^{\prime}, n$ and $L_{o p t}$ from equation (26) in equation (23), we have,

$$
\begin{equation*}
\sqrt{\lambda_{i}}=\frac{1}{C}\left\{\sqrt{\left(V_{0 i}+L_{o p t} V_{2 i}\right)\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L_{o p t}}\right)}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\} \tag{27}
\end{equation*}
$$

Thus the minimum value of $\operatorname{Var}\left(T_{i}\right) ; i=1,2,3,4$ is given as

$$
\begin{equation*}
\operatorname{Var}\left(T_{i}\right)_{\min }=\frac{1}{C}\left\{\sqrt{\left(V_{0 i}+L_{o p t} V_{2 i}\right)\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L_{o p t}}\right)}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\}^{2}-\left(\text { terms independent of } n, n^{\prime} \text { and } L\right) \tag{28}
\end{equation*}
$$

Neglecting the terms independent of $n^{\prime}, n$ and $L$, we have,

$$
\begin{equation*}
\operatorname{Var}\left(T_{i}\right)_{\min }=\frac{1}{C}\left\{\sqrt{\left(V_{0 i}+L_{o p t} V_{2 i}\right)\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L_{o p t}}\right)}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\}^{2} \tag{29}
\end{equation*}
$$

Putting the optimum value of $L$ from (26) to (29), we get the minimum value of $\operatorname{Var}\left(T_{i}\right)$ as

$$
\begin{equation*}
\operatorname{Var}\left(T_{i}\right)_{\min }=\frac{1}{C}\left\{\sqrt{V_{0 i}\left(c_{1}+c_{2} w_{1}\right)}+\sqrt{V_{0 i} w_{2} c_{3}}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\}^{2} \tag{30}
\end{equation*}
$$

## 4 Determination of $n$, $n$ and $L$ for specified variance $V=V_{0}^{\prime}$

Let $V_{0}^{\prime}$ be the variance of the estimator $T_{i}(i=1,2,3,4)$ fixed in advanced, so we have,

$$
\begin{equation*}
V_{0}^{\prime}=\frac{V_{0 i}}{n}+\frac{V_{1 i}}{n^{\prime}}+\frac{L V_{2 i}}{n}+\left(\text { terms independent of } n, n^{\prime} \text { and } L\right) ; i=1,2,3,4 \tag{31}
\end{equation*}
$$

To obtain the optimum values of $n^{\prime}, n$ and $L$ and minimizing the average total cast for the specified variance of the estimator $T_{i}$, we define a function $\psi$ given as

$$
\begin{equation*}
\psi=\left(c_{1}^{\prime}+c_{2}^{\prime}\right) n^{\prime}+n\left(c_{1}+c_{2} w_{1}+c_{3} \frac{w_{2}}{L}\right)+\mu_{i}\left(T_{i}-V_{0}^{\prime}\right) ; i=1,2,3,4 \tag{32}
\end{equation*}
$$

where $\mu_{i}$ is the Lagrange's multiplier. Partially differentiating equation (32) with respect to $n^{\prime}, n$ and $L$ and equating to zero, we get,

$$
\begin{equation*}
n^{\prime}=\sqrt{\frac{\mu_{i} V_{1 i}}{\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}}, n=\sqrt{\frac{\mu_{i}\left(V_{0 i}+L V_{2 i}\right)}{\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L}\right)}} \text { and } L_{o p t}=\sqrt{\frac{V_{0 i} w_{2} c_{3}}{V_{2 i}\left(c_{1}+c_{2} w_{1}\right)}} \tag{33}
\end{equation*}
$$

Putting the values of $n^{\prime}, n$ and $L_{o p t}$ from equation (33) in equation (31), we have,

$$
\begin{equation*}
\sqrt{\mu_{i}}=\frac{\left\{\sqrt{\left(V_{0 i}+L_{o p t} V_{2 i}\right)\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L_{o p t}}\right)}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\}}{V_{0}^{\prime}+\left(\text { terms independent of } n, n^{\prime} \text { and } L\right)} \tag{34}
\end{equation*}
$$

Thus the minimum expected total cost for the specified variance $V_{0}^{\prime}$ will be given by

$$
\begin{equation*}
C_{i(\min )}=\frac{\left\{\sqrt{\left(V_{0 i}+L_{o p t} V_{2 i}\right)\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L_{o p t}}\right)}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\}}{V_{0}^{\prime}+\left(\text { terms independent of } n, n^{\prime} \text { and } L\right)} \tag{35}
\end{equation*}
$$

Neglecting the terms independent of $n^{\prime}, n$ and $L$, we have,

$$
\begin{equation*}
C_{i(\min )}=\frac{\left\{\sqrt{\left(V_{0 i}+L_{o p t} V_{2 i}\right)\left(c_{1}+c_{2}+c_{3} \frac{w_{2}}{L_{o p t}}\right)}+\sqrt{V_{1 i}\left(c_{1}^{\prime}+c_{2}^{\prime}\right)}\right\}}{V_{0}^{\prime}} \tag{36}
\end{equation*}
$$

## 5 Empirical Study

For empirical study we consider [1] data. 25 families have been observed for the following three variabes. $y$ : Head length of second son
$x_{1}$ : Head length of first son
$x_{2}$ : Head breadth of first son
$\bar{Y}=183.84, \bar{X}_{1}=185.72, \bar{X}_{2}=151.12, C_{y}=0.0546, C_{x_{1}}=0.0526, C_{x_{2}}=0.0488$
$\rho_{y x_{1}}=0.7108, \rho_{y x_{2}}=0.6932, \rho_{x_{1} x_{2}}=0.7346$. Consider $n=7$ and $n^{\prime}=10$
The table 1 given below shows the percentage relative efficiency of $\bar{y}_{R}, \bar{y}_{r p d}$ and $T_{i}(i=1,2,3,4)$ with respect to $\bar{y}^{*}$ for the different choice of K and L .

Table 1: Percentage relative efficiency of estimators w.r.t. $\bar{y}^{*}$

| K | L | PRE of $\bar{Y}_{R}$ with <br> respect to $\bar{Y}^{*}$ | PRE of $\bar{Y}_{\text {rpd }}$ <br> with respect to <br> $\bar{Y}^{*}$ | PRE of <br> $T_{i}(i=1,2,3,4)$ <br> with respect to <br> $\bar{Y}^{*}$ |
| :---: | :---: | :--- | :--- | :--- |
| 0.1 | 2.0 | 166.44 | 180.02 | 180.02 |
|  | 2.5 | 161.61 | 173.76 | 173.76 |
|  | 3.0 | 157.43 | 168.41 | 168.41 |
|  | 3.5 | 153.78 | 163.78 | 163.78 |
| 0.2 | 2.0 | 157.43 | 168.41 | 168.41 |
|  | 2.5 | 150.56 | 159.73 | 159.73 |
|  | 3.0 | 145.17 | 153.01 | 153.01 |
|  | 3.5 | 140.81 | 147.65 | 147.65 |
| 0.3 | 2.0 | 150.56 | 159.73 | 159.73 |
|  | 2.5 | 142.88 | 150.19 | 150.19 |
|  | 3.0 | 137.22 | 143.28 | 143.28 |
|  | 3.5 | 132.88 | 138.04 | 138.04 |
| 0.4 | 2.0 | 145.17 | 153.01 | 153.01 |
|  | 2.5 | 137.22 | 143.28 | 143.28 |
|  | 3.0 | 131.65 | 136.56 | 136.56 |
|  | 3.5 | 127.53 | 131.65 | 131.65 |

## 6 Conclusion

In this paper, we have proposed ratio-cum-product type estimator in the presence of non-response under double sampling scheme. From the table 1 we conclude that the efficiency of proposed estimators are greater than that of the estimator proposed by [6] and it is same as the estimator proposed by [12]

## Acknowledgement

The authors are grateful to the anonymous referee for a careful checking of the details and for helpful comments that improved this paper.

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[^0]:    * Corresponding author e-mail: rsinghstst@gmail.com

