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# Study of Some Improved Ratio Type Estimators Under Second Order Approximation 

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#### Abstract

Chakrabarty (1979), Khoshnevisan et al. (2007), Sahai and Ray (1980), Ismail et al. (2011) and Solanki et al. (2012) proposed estimators for estimating population mean $\overline{\mathrm{Y}}$. Up to the first order of approximation and under optimum conditions, the minimum mean squared error (MSE) of all the above estimators is equal to the MSE of the regression estimator. In this paper, we have tried to found out the second order biases and mean square errors of these estimators using information on auxiliary variable based on simple random sampling. Finally, we have compared the performance of these estimators with some numerical illustration.


Keywords: Simple Random Sampling, population mean, study variable, auxiliary variable, exponential ratio type estimator, exponential product estimator, Bias and MSE.

## 1. Introduction

Let $\mathrm{U}=\left(\mathrm{U}_{1}, \mathrm{U}_{2}, \mathrm{U}_{3}, \ldots . ., \mathrm{U}_{\mathrm{i}}, \ldots . \mathrm{U}_{\mathrm{N}}\right)$ denotes a finite population of distinct and identifiable units. For estimating the population mean $\overline{\mathrm{Y}}$ of a study variable Y , let us consider X be the auxiliary variable that are correlated with study variable Y , taking the corresponding values of the units. Let a sample of size n be drawn from this population using simple random sampling without replacement (SRSWOR) and $\mathrm{y}_{\mathrm{i}}, \mathrm{xi}_{\mathrm{i}}(\mathrm{i}=1,2, \ldots . \mathrm{n})$ are the values of the study variable and auxiliary variable respectively for the i-th unit of the sample.

In sampling theory the use of suitable auxiliary information results in considerable reduction in MSE of the ratio estimators. Many authors suggested estimators using some known population parameters of an auxiliary variable. Upadhyaya and Singh (1999), Singh and Tailor (2003), Kadilar and Cingi (2006), Khoshnevisan et al. (2007), Singh et al. (2007), Singh et al. (2008) and Singh and Kumar (2011) suggested estimators in simple random sampling. Most of the authors discussed the properties of estimators along with their first order bias and MSE. Hossain et al. (2006) studied some estimators in second order approximation. In this study we have studied properties of some estimators under second order of approximation.

## 2. Some Estimators in Simple Random Sampling

For estimating the population mean $\overline{\mathrm{Y}}$ of Y , Chakrabarty (1979) proposed ratio type estimator -

$$
\begin{equation*}
t_{1}=(1-\alpha) \bar{y}+\alpha \bar{y} \frac{\bar{x}}{\bar{x}} \tag{2.1}
\end{equation*}
$$

where $\overline{\mathrm{y}}=\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{y}_{\mathrm{i}}$ and $\overline{\mathrm{x}}=\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{x}_{\mathrm{i}}$.
Khoshnevisan et al. (2007) ratio type estimator is given by

$$
\begin{equation*}
t_{2}=\bar{y}\left[\frac{\bar{x}}{\beta \bar{x}+(1-\beta) \bar{x}}\right]^{g} \tag{2.2}
\end{equation*}
$$

where $\beta$ and $g$ are constants.
Sahai and Ray (1980) proposed an estimator $\mathrm{t}_{3}$ as

$$
\begin{equation*}
\mathrm{t}_{3}=\overline{\mathrm{y}}\left[2-\left\{\frac{\overline{\mathrm{x}}}{\overline{\mathrm{x}}}\right\}^{\mathrm{w}}\right] \tag{2.3}
\end{equation*}
$$

Ismail et al. (2011) proposed and estimator t4 for estimating the population mean $\overline{\mathrm{Y}}$ of Y as

$$
\begin{equation*}
t_{4}=\bar{y}\left[\frac{\bar{x}+a(\bar{X}-\bar{x})}{\bar{x}+b(\bar{X}-\bar{x})}\right]^{p} \tag{2.4}
\end{equation*}
$$

where $\mathrm{p}, \mathrm{a}$ and b are constant.
Also, for estimating the population mean $\overline{\mathrm{Y}}$ of Y, Solanki et al. (2012) proposed an estimator $\mathrm{t}_{5}$ as

$$
\begin{equation*}
\mathrm{t}_{5}=\overline{\mathrm{y}}\left[2-\left\{\left(\frac{\overline{\mathrm{x}}}{\overline{\mathrm{x}}}\right)^{\lambda} \exp \frac{\delta(\overline{\mathrm{x}}-\overline{\mathrm{x}})}{(\overline{\mathrm{x}}+\overline{\mathrm{X}})}\right\}\right] \tag{2.5}
\end{equation*}
$$

where $\lambda$ and $\delta$ are constants, suitably chosen by minimizing mean square error of the estimator $\mathrm{t}_{5}$.

## 3. Notations used

Let us define, $e_{0}=\frac{\bar{y}-\bar{Y}}{\bar{Y}}$ and $e_{1}=\frac{\bar{x}-\bar{X}}{\bar{X}}$, then $E\left(e_{0}\right)=E\left(e_{1}\right)=0$.
For obtaining the bias and MSE the following lemmas will be used:

## Lemma 3.1

(i) $\mathrm{V}\left(\mathrm{e}_{0}\right)=\mathrm{E}\left\{\left(\mathrm{e}_{0}\right)^{2}\right\}=\frac{\mathrm{N}-\mathrm{n}}{\mathrm{N}-1} \frac{1}{\mathrm{n}} \mathrm{C}_{02}=\mathrm{L}_{1} \mathrm{C}_{02}$
(ii) $\mathrm{V}\left(\mathrm{e}_{1}\right)=\mathrm{E}\left\{\left(\mathrm{e}_{1}\right)^{2}\right\}=\frac{\mathrm{N}-\mathrm{n}}{\mathrm{N}-1} \frac{1}{\mathrm{n}} \mathrm{C}_{20}=\mathrm{L}_{1} \mathrm{C}_{20}$
(iii) $\operatorname{COV}\left(\mathrm{e}_{0}, \mathrm{e}_{1}\right)=\mathrm{E}\left\{\left(\mathrm{e}_{0} \mathrm{e}_{1}\right)\right\}=\frac{\mathrm{N}-\mathrm{n}}{\mathrm{N}-1} \frac{1}{\mathrm{n}} \mathrm{C}_{11}=\mathrm{L}_{1} \mathrm{C}_{11}$

## Lemma 3.2

(iv) $\mathrm{E}\left\{\left(\mathrm{e}_{1}^{2} \mathrm{e}_{0}\right)\right\}=\frac{(\mathrm{N}-\mathrm{n})}{(\mathrm{N}-1)} \frac{(\mathrm{N}-2 \mathrm{n})}{(\mathrm{N}-2)} \frac{1}{\mathrm{n}^{2}} \mathrm{C}_{21}=\mathrm{L}_{2} \mathrm{C}_{21}$
(v) $\mathrm{E}\left\{\left(\mathrm{e}_{1}^{3}\right)\right\}=\frac{(\mathrm{N}-\mathrm{n})}{(\mathrm{N}-1)} \frac{(\mathrm{N}-2 \mathrm{n})}{(\mathrm{N}-2)} \frac{1}{\mathrm{n}^{2}} \mathrm{C}_{30}=\mathrm{L}_{2} \mathrm{C}_{30}$

## Lemma 3.3

(vi) $\quad \mathrm{E}\left(\mathrm{e}_{1}{ }^{3} \mathrm{e}_{0}\right)=\mathrm{L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}$
(vii) $\quad \mathrm{E}\left\{\left(\mathrm{e}_{1}{ }^{4}\right)\right\}=\frac{(\mathrm{N}-\mathrm{n}))\left(\mathrm{N}^{2}+\mathrm{N}-6 \mathrm{nN}+6 \mathrm{n}^{2}\right)}{(\mathrm{N}-1)(\mathrm{N}-2)(\mathrm{N}-3)} \frac{1}{\mathrm{n}^{3}} \mathrm{C}_{30}=\mathrm{L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}{ }^{2}$
(viii) $\mathrm{E}\left(\mathrm{e}_{1}^{2} \mathrm{e}_{0}^{2}\right)=\mathrm{L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}$

Where $\quad L_{3}=\frac{(N-n)\left(N^{2}+N-6 n N+6 n^{2}\right)}{(N-1)(N-2)(N-3)} \frac{1}{n^{3}}, \quad L_{4}=\frac{N(N-n))(N-n-1)(n-1)}{(N-1)(N-2)(N-3)} \frac{1}{n^{3}}$
and $\mathrm{Cpq}=\frac{(\mathrm{Xi}-\overline{\mathrm{X}})^{\mathrm{p}}}{\overline{\mathrm{X}}^{\mathrm{p}}} \frac{\left(\mathrm{Y}_{\mathrm{i}}-\overline{\mathrm{Y}}\right)^{\mathrm{q}}}{\overline{\mathrm{Y}}^{\mathrm{q}}}$.
Proof of these lemma's are straight forward by using SRSWOR (see Sukhatme and Sukhatme (1970)).

## 4. First Order Biases and Mean Squared Errors

The expression for the biases of the estimators $t_{1}, t_{2}, t_{3}, t_{4}$ and $t_{5}$ are respectively given by

$$
\begin{align*}
& \operatorname{Bias}\left(\mathrm{t}_{1}\right)=\overline{\mathrm{Y}}\left[\frac{1}{2} \alpha \mathrm{~L}_{1} \mathrm{C}_{20}-\alpha \mathrm{L}_{1} \mathrm{C}_{11}\right]  \tag{4.1}\\
& \operatorname{Bias}\left(\mathrm{t}_{2}\right)=\overline{\mathrm{Y}}\left[\frac{\mathrm{~g}(\mathrm{~g}+1)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-g \beta L_{1} C_{11}\right]  \tag{4.2}\\
& \operatorname{Bias}\left(\mathrm{t}_{3}\right)=\overline{\mathrm{Y}}\left[-\frac{\mathrm{w}(\mathrm{w}-1)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-\mathrm{wL}_{1} \mathrm{C}_{11}\right]  \tag{4.3}\\
& \operatorname{Bias}\left(\mathrm{t}_{4}\right)=\overline{\mathrm{Y}}\left[b \mathrm{bL}_{1} \mathrm{C}_{20}-\mathrm{DL}_{1} C_{11}+\frac{\mathrm{D}(\mathrm{~b}-\mathrm{a})(\mathrm{p}-1)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}\right]  \tag{4.4}\\
& \operatorname{Bias}\left(\mathrm{t}_{5}\right)=\overline{\mathrm{Y}}\left[-\frac{\mathrm{K}(\mathrm{~K}-1)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-\mathrm{KL}_{1} \mathrm{C}_{11}\right] \tag{4.5}
\end{align*}
$$

where, $\mathrm{D}=\mathrm{p}(\mathrm{b}-\mathrm{a}) \quad$ and $\mathrm{k}=\frac{(\delta+2 \lambda)}{2}$.
Expression for the MSE's of the estimators $t_{1}, t_{2} t_{3} t_{4}$ and $t_{5}$ are, respectively given by

$$
\begin{align*}
& \operatorname{MSE}\left(\mathrm{t}_{1}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\alpha^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \alpha \mathrm{~L}_{1} \mathrm{C}_{11}\right]  \tag{4.6}\\
& \operatorname{MSE}\left(\mathrm{t}_{2}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\mathrm{g}^{2} \beta^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \mathrm{~g} \beta \mathrm{~L}_{1} \mathrm{C}_{11}\right]  \tag{4.7}\\
& \operatorname{MSE}\left(\mathrm{t}_{3}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\mathrm{w}^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \mathrm{wL}_{1} \mathrm{C}_{11}\right]  \tag{4.8}\\
& \operatorname{MSE}\left(\mathrm{t}_{4}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\mathrm{DL}_{1} \mathrm{C}_{20}-2 \mathrm{DL}_{1} \mathrm{C}_{11}\right]  \tag{4.9}\\
& \operatorname{MSE}\left(\mathrm{t}_{5}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\mathrm{k}^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \mathrm{~kL}_{1} \mathrm{C}_{11}\right] \tag{4.10}
\end{align*}
$$

## 5. Second Order Biases and Mean Squared Errors

Expressing estimator ti's (i=1,2,3,4) in terms of e's (i=0,1), we get $t_{1}=\bar{Y}\left(1+e_{0}\right)\left\{(1-\alpha)+\alpha\left(1+e_{1}\right)^{-1}\right\}$

Or

$$
\begin{equation*}
\mathrm{t}_{1}-\overline{\mathrm{Y}}=\overline{\mathrm{Y}}\left\{\mathrm{e}_{0}+\frac{\mathrm{e}_{1}}{2}+\frac{\alpha}{2} \mathrm{e}_{1}^{2}-\alpha \mathrm{e}_{0} \mathrm{e}_{1}+\alpha \mathrm{e}_{0} \mathrm{e}_{1}{ }^{2}-\frac{\alpha}{6} \mathrm{e}^{3}-\frac{\alpha}{6} \mathrm{e}_{0} \mathrm{e}_{1}^{3}+\frac{\alpha}{24} \mathrm{e}^{4}\right\} \tag{5.1}
\end{equation*}
$$

Taking expectations, we get the bias of the estimator $t_{1}$ up to the second order of approximation as

$$
\begin{gather*}
\operatorname{Bias}_{2}\left(\mathrm{t}_{1}\right)=\overline{\mathrm{Y}}\left[\frac{\alpha}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-\alpha \mathrm{L}_{1} \mathrm{C}_{11}-\frac{\alpha}{6} \mathrm{~L}_{2} \mathrm{C}_{30}+\alpha \mathrm{L}_{2} \mathrm{C}_{21}-\frac{\alpha}{6}\left(\mathrm{~L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right)\right. \\
+  \tag{5.2}\\
\left.+\frac{\alpha}{24}\left(\mathrm{~L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}^{2}\right)\right]
\end{gather*}
$$

Similarly, we get the biases of the estimator's $t_{2}, t_{3}, t_{4}$ and $t_{5}$ up to second order of approximation, respectively as

$$
\begin{align*}
\operatorname{Bias}_{2}\left(t_{2}\right)= & \bar{Y}\left[\frac{g(g+1)}{2} \beta^{2} L_{1} C_{20}-g \beta L_{1} C_{11}-\frac{g(g+1)}{2} \beta^{2} L_{2} C_{21}-\frac{g(g+1)(g+2)}{6} \beta^{3} L_{2} C_{30}\right. \\
& -\frac{g(g+1)(g+2)}{6} \beta^{3}\left(L_{3} C_{31}+3 L_{4} C_{20} C_{11}\right) \\
& \left.+\frac{g(g+1)(g+2)(g+3)}{24} \beta^{4}\left(L_{3} C_{40}+3 L_{4} C_{20}^{2}\right)\right] \tag{5.3}
\end{align*}
$$

$\operatorname{Bias}_{2}\left(\mathrm{t}_{3}\right)=\overline{\mathrm{Y}}\left[-\frac{\mathrm{w}(\mathrm{w}-1)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-\mathrm{wL}_{1} \mathrm{C}_{11}-\frac{\mathrm{w}(\mathrm{w}-1)}{2} \mathrm{~L}_{2} \mathrm{C}_{21}-\frac{\mathrm{w}(\mathrm{w}-1)(\mathrm{w}-2)}{6} \mathrm{~L}_{2} \mathrm{C}_{30}\right.$

$$
\begin{align*}
& -\frac{\mathrm{w}(\mathrm{w}-1)(\mathrm{w}-2)}{6}\left(\mathrm{~L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right) \\
& \left.-\frac{\mathrm{w}(\mathrm{w}-1)(\mathrm{w}-2)(\mathrm{w}-3)}{24}\left(\mathrm{~L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}{ }^{2}\right)\right] \tag{5.4}
\end{align*}
$$

$$
\begin{align*}
& \operatorname{Bias}_{2}\left(\mathrm{t}_{4}\right)=\overline{\mathrm{Y}}\left[\frac{\left(\mathrm{D}_{1} \mathrm{bD}\right)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-\mathrm{DL}_{1} \mathrm{C}_{11}+\frac{\left(\mathrm{bD}+\mathrm{D}_{1}\right)}{} \mathrm{L}_{2} \mathrm{C}_{21}-\frac{\left(\mathrm{b}^{2} \mathrm{D}+2 \mathrm{bD}+\mathrm{D}_{2}\right)}{} \mathrm{L}_{2} \mathrm{C}_{30}\right. \\
&-\left(\mathrm{b}^{2} \mathrm{D}+2 \mathrm{bD}_{1}\right)\left(\mathrm{L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right) \\
&\left.+\frac{\left(\mathrm{b}^{3} \mathrm{D}+3 \mathrm{~b}^{2} \mathrm{D}_{1}+3 \mathrm{bD}_{2}+\mathrm{D}_{3}\right)}{}\left(\mathrm{L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}^{2}\right)\right] \tag{5.5}
\end{align*}
$$

where,
$D_{1}=D \frac{(b-a)(p-1)}{2}$
$\mathrm{D}_{2}=\mathrm{D}_{1} \frac{(\mathrm{~b}-\mathrm{a})(\mathrm{p}-2)}{3}$.
$\operatorname{Bias}_{2}\left(\mathrm{t}_{5}\right)=\overline{\mathrm{Y}}\left[-\frac{\mathrm{k}(\mathrm{k}-1)}{2} \mathrm{~L}_{1} \mathrm{C}_{20}-\mathrm{kL}_{1} \mathrm{C}_{11}-\frac{\mathrm{k}(\mathrm{k}-1)}{2} \mathrm{~L}_{2} \mathrm{C}_{21}-\mathrm{ML}_{2} \mathrm{C}_{30}-\mathrm{M}\left(\mathrm{L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right)\right.$

$$
\begin{equation*}
-\mathrm{N}\left(\mathrm{~L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}{ }^{2}\right) \tag{5.6}
\end{equation*}
$$

Where, $\mathrm{M}=\frac{1}{2}\left\{\frac{\left(\delta^{3}-6 \delta^{2}\right)}{24}+\frac{\left(\alpha\left(\delta^{2}-2 \delta\right)\right.}{4}+\frac{\lambda(\lambda-1)}{2} \delta+\frac{\lambda(\lambda-1)(\lambda-2)}{3}\right\}$,

$$
\begin{gathered}
\mathrm{k}=\frac{(\delta+2 \lambda)}{2} \\
\mathrm{~N}=\frac{1}{8}\left\{\frac{\left(\delta^{4}-12 \delta^{3}+12 \delta^{2}\right)}{48}+\frac{\left(\alpha\left(\delta^{3}-6 \delta\right)\right.}{6}+\frac{\lambda(\lambda-1)}{2}\left(\delta^{2}-2 \delta\right)+\frac{\lambda(\lambda-1)(\lambda-2)(\lambda-3)}{3}\right\} .
\end{gathered}
$$

The MSE's of the estimators $t_{1}, t_{2}, t_{3}, t_{4}$ and $t_{5}$ up to the second order of approximation are, respectively given by

$$
\begin{align*}
& \operatorname{MSE}_{2}\left(\mathrm{t}_{1}\right)= \overline{\mathrm{Y}}^{2}\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\alpha^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \alpha \mathrm{~L}_{1} \mathrm{C}_{11}-\alpha^{2} \mathrm{~L}_{2} \mathrm{C}_{30}+\left(2 \alpha^{2}+\alpha\right) \mathrm{L}_{2} \mathrm{C}_{21}\right. \\
&-2 \alpha^{2}\left(\mathrm{~L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right) \\
&\left.+\alpha(\alpha+1)\left(\mathrm{L}_{3} \mathrm{C}_{22}+3 \mathrm{~L}_{4}\left(\mathrm{C}_{20} \mathrm{C}_{02}+\mathrm{C}_{11}^{2}\right)\right)+\frac{5}{24} \alpha^{2}\left(\mathrm{~L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}^{2}\right)\right]  \tag{5.7}\\
& \operatorname{MSE}_{2}\left(\mathrm{t}_{2}\right)=\overline{\mathrm{Y}}^{2} \mid \mathrm{L}_{1} \mathrm{C}_{02}+\mathrm{g}^{2} \beta^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \beta \mathrm{gL}_{1} \mathrm{C}_{11}-\beta^{3} \mathrm{~g}^{2}(\mathrm{~g}+1) \mathrm{L}_{2} \mathrm{C}_{30}+\mathrm{g}(3 \mathrm{~g}+1) \beta^{2} \mathrm{~L}_{2} \mathrm{C}_{21} \\
&-2 \beta \mathrm{gL}_{2} \mathrm{C}_{12}-\left\{\frac{7 \mathrm{~g}^{3}+9 \mathrm{~g}^{2}+2 \mathrm{~g}}{3}\right\} \beta^{3}\left(\mathrm{~L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right) \\
&+\mathrm{g}(2 \mathrm{~g}+1) \beta^{2}\left(\mathrm{~L}_{3} \mathrm{C}_{22}+3 \mathrm{~L}_{4}\left(\mathrm{C}_{20} \mathrm{C}_{02}+\mathrm{C}_{11}^{2}\right)\right) \\
&+\left\{\frac{2 \mathrm{~g}^{3}+9 \mathrm{~g}^{2}+10 \mathrm{~g}+3}{6}\right\} \beta^{4}\left(\mathrm{~L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}^{2}\right] \tag{5.8}
\end{align*}
$$

$$
\begin{align*}
\operatorname{MSE}_{2}\left(\mathrm{t}_{3}\right)= & \overline{\mathrm{Y}}^{2}
\end{aligned} \begin{aligned}
& {\left[\mathrm{L}_{1} \mathrm{C}_{02}+\mathrm{w}^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \mathrm{wL}_{1} \mathrm{C}_{11}-\mathrm{w}^{2}(\mathrm{w}-1) \mathrm{L}_{2} \mathrm{C}_{30}+\mathrm{w}(\mathrm{w}+1) \mathrm{L}_{2} \mathrm{C}_{21}-2 \mathrm{wL}_{2} \mathrm{C}_{12}\right.} \\
& +\left\{\frac{5 \mathrm{w}^{3}-3 \mathrm{w}^{2}-2 \mathrm{w}}{3}\right\}\left(\mathrm{L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right) \\
& \left.+\mathrm{w}\left(\mathrm{~L}_{3} \mathrm{C}_{22}+3 \mathrm{~L}_{4}\left(\mathrm{C}_{20} \mathrm{C}_{02}+\mathrm{C}_{11}^{2}\right)\right)+\left\{\frac{7 \mathrm{w}^{4}-18 \mathrm{w}^{3}+11 \mathrm{w}^{2}}{24}\right\}\left(\mathrm{L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}{ }^{2}\right)\right] \tag{5.9}
\end{align*}
$$

$$
\begin{align*}
& \operatorname{MSE}_{2}\left(\mathrm{t}_{4}\right)=\overline{\mathrm{Y}}^{2} \mid \mathrm{L}_{1} \mathrm{C}_{02}+\mathrm{D}^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \mathrm{DL}_{1} \mathrm{C}_{11}-4 \mathrm{DD}_{1} \mathrm{~L}_{2} \mathrm{C}_{30}+\left(2 \mathrm{bD}+2 \mathrm{D}_{1}+2 \mathrm{D}^{2}\right) \mathrm{L}_{2} \mathrm{C}_{21}-2 \mathrm{DL}_{2} \mathrm{C}_{12} \\
& +\left\{2 \mathrm{D}^{2}+2 \mathrm{~b}^{2} \mathrm{D}+2 \mathrm{DD}_{1}+4 \mathrm{bD} \mathrm{D}_{1}+4 \mathrm{bD}^{2}\right\}\left(\mathrm{L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right) \\
& +\left\{D^{2}+2 D_{1}+2 b D\right\}\left(L_{3} C_{22}+3 L_{4}\left(C_{20} C_{02}+C_{11}^{2}\right)\right) \\
& \left.+\left\{3 \mathrm{~b}^{2} \mathrm{D}^{2}+\mathrm{D}_{1}^{2}+2 \mathrm{DD}_{2}+12 \mathrm{bDD}_{1}\right\}\left(\mathrm{L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}^{2}\right)\right] \tag{5.10}
\end{align*}
$$

$$
\begin{align*}
\operatorname{MSE}_{2}\left(\mathrm{t}_{5}\right)=\overline{\mathrm{Y}}^{2} & {\left[\mathrm{~L}_{1} \mathrm{C}_{02}+\mathrm{k}^{2} \mathrm{~L}_{1} \mathrm{C}_{20}-2 \mathrm{~kL}_{1} \mathrm{C}_{11}+\mathrm{kL}_{2} \mathrm{C}_{21}-2 \mathrm{~kL}_{2} \mathrm{C}_{12}+\mathrm{k}^{2}(\mathrm{k}-1) \mathrm{L}_{2} \mathrm{C}_{30}\right.} \\
& +2 \mathrm{k}^{2}(\mathrm{k}-1)\left(\mathrm{L}_{3} \mathrm{C}_{31}+3 \mathrm{~L}_{4} \mathrm{C}_{20} \mathrm{C}_{11}\right)+\mathrm{k}\left(\mathrm{~L}_{3} \mathrm{C}_{22}+3 \mathrm{~L}_{4}\left(\mathrm{C}_{20} \mathrm{C}_{02}+\mathrm{C}_{11}^{2}\right)\right) \\
& \left.+\frac{\left(\mathrm{k}^{2}-\mathrm{k}\right)^{2}}{4}\left(\mathrm{~L}_{3} \mathrm{C}_{40}+3 \mathrm{~L}_{4} \mathrm{C}_{20}^{2}\right)\right] \tag{5.11}
\end{align*}
$$

## 6. Numerical Illustration

For a natural population data, we have calculated the biases and the mean square error's of the estimator's and compare these biases and MSE's of the estimator's under first and second order of approximations.

## Data Set

The data for the empirical analysis are taken from 1981, Utter Pradesh District Census Handbook, Aligar. The population consist of 340 villages under koil police station, with $\mathrm{Y}=$ Number of agricultural labour in 1981 and $\mathrm{X}=$ Area of the villages (in acre) in 1981. The following values are obtained

$$
\begin{aligned}
& \overline{\mathrm{Y}}=73.76765, \overline{\mathrm{X}}=2419.04, \mathrm{~N}=340, \mathrm{n}=70, \mathrm{n}^{\prime}=120, \mathrm{n}=70, \mathrm{C}_{02}=0.7614, \mathrm{C}_{11}=0.2667, \\
& \mathrm{C}_{03}=2.6942, \mathrm{C}_{12}=0.0747, \mathrm{C}_{12}=0.1589, \mathrm{C}_{30}=0.7877, \mathrm{C}_{13}=0.1321, \mathrm{C}_{31}=0.8851, \mathrm{C}_{04}=17.4275 \\
& \mathrm{C}_{22}=0.8424, \mathrm{C}_{40}=1.3051
\end{aligned}
$$

Table 6.1: Biases and MSE's of the estimators

| Estimator | Bias |  | MSE |  |
| :---: | :---: | :---: | :---: | :---: |
|  | First order | Second order | First order | Second order |
| $t_{1}$ | 0.0044915 | 0.004424 | 39.217225 | 39.45222 |
| $t_{2}$ | 0 | -0.00036 | 39.217225 <br> (for $\mathrm{g}=1)$ | 39.33552 <br> (for $\mathrm{g}=1)$ |
| $\mathrm{t}_{3}$ | -0.04922 | -0.04935 | 39.217225 | 39.29102 |
| $\mathrm{t}_{4}$ | 0.2809243 | -0.60428 | 39.217225 | 39.44855 |
| $\mathrm{t}_{5}$ | -0.027679 | -0.04911 | 39.217225 | 39.27187 |

In the Table 6.1 the biases and MSE's of the estimators $t_{1}, t_{2}, t_{3}, t_{4}$ and $t_{5}$ are written under first order and second order of approximations. For all the estimators $t 1, t_{2}, t_{3}, t_{4}$ and $t_{5}$, it was observed that the value of the biases decreased and the value of the MSE's increased for second order approximation. MSE's of the estimators up to the first order of approximation under optimum conditions are same. From Table 6.1 we observe that under
second order of approximation the estimator $t_{5}$ is best followed by $t_{3}$, and $t_{2}$ among the estimators considered here for the given data set.

## 7. Estimators under stratified random sampling

In survey sampling, it is well established that the use of auxiliary information results in substantial gain in efficiency over the estimators which do not use such information. However, in planning surveys, the stratified sampling has often proved needful in improving the precision of estimates over simple random sampling. Assume that the population U consist of $L$ strata as $U=U_{1}, U_{2}, \ldots, U_{L}$. Here the size of the stratum $U_{h}$ is $N_{h}$, and the size of simple random sample in stratum $\mathrm{U}_{\mathrm{h}}$ is $\mathrm{n}_{\mathrm{h}}$, where $\mathrm{h}=1,2$,---,L.

The Chakrabarty(1979) ratio- type estimator under stratified random sampling is given by

$$
\begin{equation*}
\mathrm{t}_{1}^{\prime}=(1-\alpha) \overline{\mathrm{y}}_{\mathrm{st}}+\alpha \overline{\mathrm{y}}_{\mathrm{st}} \frac{\overline{\mathrm{X}}}{\overline{\mathrm{x}}_{\mathrm{st}}} \tag{7.1}
\end{equation*}
$$

where,

$$
\begin{aligned}
& \overline{\mathrm{y}}_{\mathrm{h}}=\frac{1}{\mathrm{n}_{\mathrm{h}}} \sum_{\mathrm{i}=1}^{\mathrm{n}_{\mathrm{h}}} \mathrm{y}_{\mathrm{hi}}, \quad \overline{\mathrm{x}}_{\mathrm{h}}=\frac{1}{\mathrm{n}_{\mathrm{h}}} \sum_{\mathrm{i}=1}^{\mathrm{n}_{\mathrm{h}}} \mathrm{x}_{\mathrm{hi}}, \\
& \overline{\mathrm{y}}_{\mathrm{st}}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{w}_{\mathrm{h}} \overline{\mathrm{y}}_{\mathrm{h}}, \quad \overline{\mathrm{x}}_{\mathrm{st}}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{w}_{\mathrm{h}} \overline{\mathrm{x}}_{\mathrm{h}}, \quad \text { and } \quad \overline{\mathrm{x}}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{w}_{\mathrm{h}} \overline{\mathrm{x}}_{\mathrm{h}} .
\end{aligned}
$$

Khoshnevisan et al. (2007) ratio- type estimator under stratified random sampling is given by

$$
\begin{equation*}
\mathrm{t}_{2}^{\prime}=\overline{\mathrm{y}}_{\mathrm{st}}\left[\frac{\overline{\mathrm{X}}}{\beta \overline{\mathrm{x}}_{\mathrm{st}}+(1-\beta) \overline{\mathrm{X}}}\right]^{\mathrm{g}} \tag{7.2}
\end{equation*}
$$

where g is a constant, for $\mathrm{g}=1, \mathrm{t}_{2}^{\prime}$ is same as conventional ratio estimator whereas for $\mathrm{g}=-$ 1, it becomes conventional product type estimator.
Sahai and Ray (1980) estimator $t_{3}$ under stratified random sampling is given by

$$
\begin{equation*}
\mathrm{t}_{3}^{\prime}=\overline{\mathrm{y}}_{\mathrm{st}}\left[2-\left\{\frac{\overline{\mathrm{x}}_{\mathrm{st}}}{\overline{\mathrm{x}}}\right\}^{\mathrm{w}}\right] \tag{7.3}
\end{equation*}
$$

Ismail et al. (2011) estimator under stratified random sampling $\mathrm{t}_{4}^{\prime}$ is given by

$$
\begin{equation*}
\mathrm{t}_{4}^{\prime}=\overline{\mathrm{y}}_{\mathrm{st}}\left[\frac{\overline{\mathrm{x}}+\mathrm{a}\left(\overline{\mathrm{X}}-\overline{\mathrm{x}}_{\mathrm{st}}\right)}{\overline{\mathrm{x}}+\mathrm{b}\left(\overline{\mathrm{X}}-\overline{\mathrm{x}}_{\mathrm{st}}\right)}\right]^{\mathrm{p}} \tag{7.4}
\end{equation*}
$$

Solanki et al. (2012) estimator under stratified random sampling is given as

$$
\begin{equation*}
\mathrm{t}_{5}^{\prime}=\overline{\mathrm{y}}_{\mathrm{st}}\left[2-\left\{\left(\frac{\overline{\mathrm{x}}_{\mathrm{st}}}{\overline{\mathrm{X}}}\right)^{\lambda} \exp \frac{\delta\left(\overline{\mathrm{x}}_{\mathrm{st}}-\overline{\mathrm{x}}\right)}{\left(\overline{\mathrm{x}}_{\mathrm{st}}+\overline{\mathrm{X}}\right)}\right\}\right] \tag{7.5}
\end{equation*}
$$

where $\lambda$ and $\delta$ are the constants, suitably chosen by minimizing MSE of the estimator $\mathrm{t}_{5}^{\prime}$.

## 8. Notations used under stratified random sampling

Let us define, $e_{0}=\frac{\bar{y}_{s t}-\bar{y}}{\bar{y}}$ and $e_{1}=\frac{\bar{x}_{s t}-\bar{x}}{\bar{x}}$, then $E\left(e_{0}\right)=E\left(e_{1}\right)=0$.

To obtain the bias and MSE of the proposed estimators, we use the following notations in the rest of the article:

$$
\begin{aligned}
& y_{n t}=\Sigma \sum_{h=1} w_{h} g_{h}=\bar{P}\left(1+g_{0}\right)_{v}
\end{aligned}
$$

such that,

$$
\begin{array}{r}
\mathbb{E}\left(\mathrm{s}_{0}\right)=\mathbb{E}\left(\mathrm{e}_{1}\right)=\mathbb{E}\left(\mathrm{e}_{2}\right)=0_{t} \text { and } \\
\mathrm{V}_{\mathrm{rs}}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{~W}_{\mathrm{h}}^{\mathrm{rts}} \mathrm{E}\left[\left(\overline{\mathrm{x}}_{\mathrm{h}}-\overline{\mathrm{X}}_{\mathrm{h}}\right)^{\mathrm{r}}\left(\overline{\mathrm{y}}_{\mathrm{h}}-\overline{\mathrm{Y}}_{\mathrm{h}}\right)^{\mathrm{s}}\right]
\end{array}
$$

Also

$$
\begin{aligned}
& \mathrm{E}\left(\mathrm{e}_{0}^{2}\right)=\frac{\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{w}_{\mathrm{h}}^{2} \gamma_{\mathrm{h}} \mathrm{~S}_{\mathrm{yh}}^{2}}{\overline{\mathrm{Y}}^{2}}=\mathrm{V}_{20} \\
& \mathrm{E}\left(\mathrm{e}_{1}^{2}\right)=\frac{\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{w}_{\mathrm{h}}^{2} \gamma_{\mathrm{h}} \mathrm{~S}_{\mathrm{xyh}}^{2}}{\overline{\mathrm{X}}^{2}}=\mathrm{V}_{02}
\end{aligned}
$$

$$
E\left(e_{0} e_{1}\right)=\frac{\sum_{h=1}^{L} w_{h}^{2} \gamma_{h} S_{x y h}^{2}}{\overline{X Y}}=V_{11}
$$

Where

$$
\begin{array}{lll}
S_{y h}^{2}=\frac{\sum_{i=1}^{N_{h}}\left(\overline{\mathrm{y}}_{\mathrm{h}}-\overline{\mathrm{Y}}_{\mathrm{h}}\right)^{2}}{N_{\mathrm{h}}-1}, & \mathrm{~S}_{\mathrm{xh}}^{2}=\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}_{\mathrm{h}}}\left(\overline{\mathrm{x}}_{\mathrm{h}}-\overline{\mathrm{X}}_{\mathrm{h}}\right)^{2}}{\mathrm{~N}_{\mathrm{h}}-1}, & \mathrm{~S}_{\mathrm{xyh}}=\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}_{\mathrm{h}}}\left(\overline{\mathrm{x}}_{\mathrm{h}-} \overline{\mathrm{X}}_{\mathrm{h}}\right)\left(\overline{\mathrm{y}}_{\mathrm{h}}-\overline{\mathrm{Y}}_{\mathrm{h}}\right)}{\mathrm{N}_{\mathrm{h}}-1} \\
\gamma_{\mathrm{h}}=\frac{1-\mathrm{f}_{\mathrm{h}}}{\mathrm{n}_{\mathrm{h}}}, & \mathrm{f}_{\mathrm{h}}=\frac{\mathrm{n}_{\mathrm{h}}}{\mathrm{~N}_{\mathrm{h}}}, & \mathrm{w}_{\mathrm{h}}=\frac{\mathrm{N}_{\mathrm{h}}}{\mathrm{n}_{\mathrm{h}}} .
\end{array}
$$

Some additional notations for second order approximation,

$$
\mathrm{V}_{\mathrm{rs}}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{~W}_{\mathrm{h}}^{\mathrm{r}+\mathrm{s}} \frac{1}{\overline{\mathrm{Y}}^{\mathrm{r}} \overline{\mathrm{X}}^{\mathrm{s}}} \mathrm{E}\left[\left(\overline{\mathrm{y}}_{\mathrm{h}}-\overline{\mathrm{Y}}_{\mathrm{h}}\right)^{\mathrm{s}}\left(\overline{\mathrm{x}}_{\mathrm{h}}-\overline{\mathrm{X}}_{\mathrm{h}}\right)^{\mathrm{r}}\right]
$$

Where,

$$
\begin{aligned}
& C_{r s(h)}=\frac{1}{N_{h}} \sum_{\mathrm{i}=1}^{\mathrm{N}_{\mathrm{h}}}\left[\left(\overline{\mathrm{y}}_{\mathrm{h}}-\overline{\mathrm{Y}}_{\mathrm{h}}\right)^{\mathrm{s}}\left(\overline{\mathrm{x}}_{\mathrm{h}}-\overline{\mathrm{X}}_{\mathrm{h}}\right)^{\mathrm{r}}\right] \\
& V_{12}=\sum_{h=1}^{L} W_{h}^{3} \frac{k_{1(h)} C_{12(h))}}{\bar{Y} X^{2}} \quad V_{21}=\sum_{h=1}^{L} W_{h}^{3} \frac{k_{1(h)} C_{21(h)}}{\bar{Y}^{2} \bar{X}} \quad V_{30}=\sum_{h=1}^{L} W_{h}^{3} \frac{k_{1(h)} C_{30(h)}}{\bar{Y}^{3}} \\
& \mathrm{~V}_{03}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{~W}_{\mathrm{h}}^{3} \frac{\mathrm{k}_{1(\mathrm{~h}} \mathrm{C}_{03(\mathrm{~h})}}{\overline{\mathrm{X}}^{3}} \quad \mathrm{~V}_{13}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{~W}_{\mathrm{h}}^{4} \frac{\mathrm{k}_{2(\mathrm{~h})} \mathrm{C}_{13(\mathrm{~h})}+3 \mathrm{k}_{3(\mathrm{~h})} \mathrm{C}_{01(\mathrm{~h})} \mathrm{C}_{02(\mathrm{~h})}}{\overline{\mathrm{YX}}^{3}} \\
& \mathrm{~V}_{04}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{~W}_{\mathrm{h}}^{4} \frac{\mathrm{k}_{2(\mathrm{~h})} \mathrm{C}_{04(\mathrm{~h})}+3 \mathrm{k}_{3(\mathrm{~h})} \mathrm{C}_{02(\mathrm{~h})}^{2}}{\overline{\mathrm{X}}^{4}} \\
& \mathrm{~V}_{22}=\sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{~W}_{\mathrm{h}}^{4} \frac{\mathrm{k}_{2(\mathrm{~h})} \mathrm{C}_{22(\mathrm{~h})}+\mathrm{k}_{3(\mathrm{~h})}\left(\mathrm{C}_{01(\mathrm{~h})} \mathrm{C}_{02(\mathrm{~h})}+2 \mathrm{C}_{11(\mathrm{~h})}^{2}\right)}{\overline{\mathrm{Y}}^{2} \overline{\mathrm{X}}^{2}}
\end{aligned}
$$

Where

$$
\begin{aligned}
& \mathrm{k}_{1(\mathrm{~h})}=\frac{\left(\mathrm{N}_{\mathrm{h}}-\mathrm{n}_{\mathrm{h}}\right)\left(\mathrm{N}_{\mathrm{h}}-2 \mathrm{n}_{\mathrm{h}}\right)}{\mathrm{n}^{2}\left(\mathrm{~N}_{\mathrm{h}}-1\right)\left(\mathrm{N}_{\mathrm{h}}-2\right)} \\
& \mathrm{k}_{2(\mathrm{~h})}=\frac{\left(\mathrm{N}_{\mathrm{h}}-\mathrm{n}_{\mathrm{h}}\right)\left(\mathrm{N}_{\mathrm{h}}+1\right) \mathrm{N}_{\mathrm{h}}-6 \mathrm{n}_{\mathrm{h}}\left(\mathrm{~N}_{\mathrm{h}}-\mathrm{n}_{\mathrm{h}}\right)}{\mathrm{n}^{3}\left(\mathrm{~N}_{\mathrm{h}}-1\right)\left(\mathrm{N}_{\mathrm{h}}-2\right)\left(\mathrm{N}_{\mathrm{h}}-3\right)} \\
& \mathrm{k}_{3(\mathrm{~h})}=\frac{\left(\mathrm{N}_{\mathrm{h}}-\mathrm{n}_{\mathrm{h}}\right) \mathrm{N}_{\mathrm{h}}\left(\mathrm{~N}_{\mathrm{h}}-\mathrm{n}_{\mathrm{h}}-1\right)\left(\mathrm{n}_{\mathrm{h}}-1\right)}{\mathrm{n}^{3}\left(\mathrm{~N}_{\mathrm{h}}-1\right)\left(\mathrm{N}_{\mathrm{h}}-2\right)\left(\mathrm{N}_{\mathrm{h}}-3\right)}
\end{aligned}
$$

## 9. First Order Biases and Mean Squared Errors

The biases of the estimators $\mathfrak{t}_{1}^{\prime}, t_{2}^{\prime}, t_{3}^{\prime}, t_{4}^{\prime}$ and $t_{5}^{\prime}$ are respectively given by

$$
\begin{align*}
& \operatorname{Bias}\left(\mathrm{t}_{1}^{\prime}\right)=\overline{\mathrm{Y}}\left[\frac{1}{2} \alpha \mathrm{~L}_{1} \mathrm{~V}_{02}-\alpha \mathrm{V}_{11}\right]  \tag{9.1}\\
& \operatorname{Bias}\left(\mathrm{t}_{2}^{\prime}\right)=\overline{\mathrm{Y}}\left[\frac{\mathrm{~g}(\mathrm{~g}+1)}{2} \beta^{2} \mathrm{~V}_{02}-\mathrm{g} \beta \mathrm{~V}_{11}\right]  \tag{9.2}\\
& \operatorname{Bias}\left(\mathrm{t}_{3}^{\prime}\right)=\overline{\mathrm{Y}}\left[-\frac{\mathrm{w}(\mathrm{w}-1)}{2} \mathrm{~V}_{02}-\mathrm{w} \mathrm{~V}_{11}\right]  \tag{9.3}\\
& \operatorname{Bias}\left(\mathrm{t}_{4}^{\prime}\right)=\overline{\mathrm{Y}}\left[\mathrm{bDV}_{02}-D V_{11}+\frac{\mathrm{D}(\mathrm{~b}-\mathrm{a})(\mathrm{p}-1)}{2} V_{02}\right]  \tag{9.4}\\
& \operatorname{Bias}\left(\mathrm{t}_{5}^{\prime}\right)=\overline{\mathrm{Y}}\left[-\frac{\mathrm{K}(\mathrm{~K}-1)}{2} \mathrm{~V}_{02}-K V_{11}\right] \tag{9.5}
\end{align*}
$$

Where, $\mathrm{D}=\mathrm{p}(\mathrm{b}-\mathrm{a}) \quad$ and $\mathrm{k}=\frac{(\delta+2 \lambda)}{2}$.
The MSE's of the estimators $t_{1}^{\prime}, t_{2}^{\prime}, t_{3}^{\prime}, t_{4}^{\prime}$ and $t_{5}^{\prime}$ are respectively given by

$$
\begin{align*}
& \operatorname{MSE}\left(\mathrm{t}_{1}^{\prime}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\alpha^{2} \mathrm{~V}_{02}-2 \alpha \mathrm{~V}_{11}\right]  \tag{9.6}\\
& \operatorname{MSE}\left(\mathrm{t}_{2}^{\prime}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\mathrm{g}^{2} \beta^{2} \mathrm{~V}_{02}-2 \mathrm{~g} \beta \mathrm{~V}_{11}\right]  \tag{9.7}\\
& \operatorname{MSE}\left(\mathrm{t}_{3}^{\prime}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\mathrm{w}^{2} \mathrm{~V}_{02}-2 \mathrm{wV}_{11}\right]  \tag{9.8}\\
& \operatorname{MSE}\left(\mathrm{t}_{4}^{\prime}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\mathrm{DV}_{02}-2 \mathrm{DV}_{11}\right]  \tag{9.9}\\
& \operatorname{MSE}\left(\mathrm{t}_{5}^{\prime}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\mathrm{k}^{2} \mathrm{~V}_{02}-2 \mathrm{k} \mathrm{~V}_{11}\right] \tag{9.10}
\end{align*}
$$

## 10. Second Order Biases and Mean Squared Errors

Expressing estimator $\mathrm{t}_{\mathrm{i}}$ 's $(\mathrm{i}=1,2,3,4)$ in terms of e's $(\mathrm{i}=0,1)$, we get $\mathrm{t}_{1}^{\prime}=\overline{\mathrm{Y}}\left(1+\mathrm{e}_{0}\right)\left\{(1-\alpha)+\alpha\left(1+\mathrm{e}_{1}\right)^{-1}\right\}$

Or
$t_{1}^{\prime}-\bar{Y}=\bar{Y}\left\{e_{0}+\frac{e_{1}}{2}+\frac{\alpha}{2} e_{1}{ }^{2}-\alpha e_{0} e_{1}+\alpha e_{0} e_{1}{ }^{2}-\frac{\alpha}{6} e^{3}-\frac{\alpha}{6} e_{0} e_{1}{ }^{3}+\frac{\alpha}{24} e^{4}\right\}$

Taking expectations, we get the bias of the estimator $t_{1}^{\prime}$ up to the second order of approximation as
$\operatorname{Bias}_{2}\left(\mathrm{t}_{1}^{\prime}\right)=\overline{\mathrm{Y}}\left[\frac{\alpha}{2} \mathrm{~V}_{02}-\alpha \mathrm{V}_{11}-\frac{\alpha}{6} \mathrm{~V}_{03}+\alpha \mathrm{V}_{12}-\frac{\alpha}{6} \mathrm{~V}_{13}+\frac{\alpha}{24} \mathrm{~V}_{04}\right]$
Similarly we get the Biases of the estimator's $\mathrm{t}_{2}^{\prime}, \mathrm{t}_{3}^{\prime}, \mathrm{t}_{4}^{\prime}$ and $\mathrm{t}_{5}^{\prime}$ up to second order of approximation, respectively as
$\operatorname{Bias}_{2}\left(\mathrm{t}_{2}^{\prime}\right)=\overline{\mathrm{Y}}\left[\frac{g(g+1)}{2} \beta^{2} V_{02}-g \beta V_{11}-\frac{g(g+1)}{2} \beta^{2} V_{12}-\frac{g(g+1)(g+2)}{6} \beta^{3} V_{30}\right.$

$$
\begin{equation*}
\left.-\frac{g(g+1)(g+2)}{6} \beta^{3} V_{31}+\frac{g(g+1)(g+2)(g+3)}{24} \beta^{4} V_{04}\right] \tag{10.3}
\end{equation*}
$$

$$
\begin{align*}
\operatorname{Bias}_{2}\left(\mathrm{t}_{3}^{\prime}\right)= & \overline{\mathrm{Y}}
\end{aligned} \begin{aligned}
& -\frac{\mathrm{w}(\mathrm{w}-1)}{2} \mathrm{~V}_{02}-\mathrm{wV}_{11}-\frac{\mathrm{w}(\mathrm{w}-1)}{2} \mathrm{~V}_{12}-\frac{\mathrm{w}(\mathrm{w}-1)(\mathrm{w}-2)}{6} \mathrm{~V}_{03} \\
& \left.-\frac{\mathrm{w}(\mathrm{w}-1)(\mathrm{w}-2)}{6} \mathrm{~V}_{31}-\frac{\mathrm{w}(\mathrm{w}-1)(\mathrm{w}-2)(\mathrm{w}-3)}{24} V_{04}\right] \tag{10.4}
\end{align*}
$$

$\operatorname{Bias}_{2}\left(\mathrm{t}_{4}^{\prime}\right)=\overline{\mathrm{Y}}\left[\frac{\left(\mathrm{D}_{1} \mathrm{bD}\right)}{2} \mathrm{~V}_{02}-\mathrm{DV}_{11}+\left(\mathrm{bD}+\mathrm{D}_{1}\right) \mathrm{V}_{12}-\left(\mathrm{b}^{2} \mathrm{D}+2 \mathrm{bD} \mathrm{D}_{1}+\mathrm{D}_{2}\right) \mathrm{V}_{03}\right.$

$$
\begin{equation*}
\left.-\left(b^{2} D+2 b D_{1}\right) V_{31}+\left(b^{3} D+3 b^{2} D_{1}+3 b D_{2}+D_{3}\right) V_{04}\right\rfloor \tag{10.5}
\end{equation*}
$$

Where,
$D=p(b-a)$
$D_{1}=D \frac{(b-a)(p-1)}{2}$
$\mathrm{D}_{2}=\mathrm{D}_{1} \frac{(\mathrm{~b}-\mathrm{a})(\mathrm{p}-2)}{3}$
$\operatorname{Bias}_{2}\left(\mathrm{t}_{5}^{\prime}\right)=\overline{\mathrm{Y}}\left[\left[-\frac{\mathrm{k}(\mathrm{k}-1)}{2} \mathrm{~V}_{02}-\mathrm{kV} V_{11}-\frac{\mathrm{k}(\mathrm{k}-1)}{2} \mathrm{~V}_{12}-\mathrm{MV}_{03}-\mathrm{MV}_{31}-N V_{04}\right]\right.$

Where, $\mathrm{M}=\frac{1}{2}\left\{\frac{\left(\delta^{3}-6 \delta^{2}\right)}{24}+\frac{\left(\alpha\left(\delta^{2}-2 \delta\right)\right.}{4}+\frac{\lambda(\lambda-1)}{2} \delta+\frac{\lambda(\lambda-1)(\lambda-2)}{3}\right\}, \quad \mathrm{k}=\frac{(\delta+2 \lambda)}{2}$

$$
\mathrm{N}=\frac{1}{8}\left\{\frac{\left(\delta^{4}-12 \delta^{3}+12 \delta^{2}\right)}{48}+\frac{\left(\alpha\left(\delta^{3}-6 \delta\right)\right.}{6}+\frac{\lambda(\lambda-1)}{2}\left(\delta^{2}-2 \delta\right)+\frac{\lambda(\lambda-1)(\lambda-2)(\lambda-3)}{3}\right\}
$$

Following are the MSE of the estimators $\mathrm{t}_{1}^{\prime}, \mathrm{t}_{2}^{\prime}, \mathrm{t}_{3}^{\prime}, \mathrm{t}_{4}^{\prime}$ and $\mathrm{t}_{5}^{\prime} \mathrm{up}$ to second order of approximation

$$
\begin{align*}
\operatorname{MSE}_{2}\left(\mathrm{t}_{1}^{\prime}\right)= & \overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\alpha^{2} \mathrm{~V}_{02}-2 \alpha \mathrm{~V}_{11}-\alpha^{2} \mathrm{~V}_{03}+\left(2 \alpha^{2}+\alpha\right) \mathrm{V}_{12}\right. \\
& \left.-2 \alpha^{2} \mathrm{~V}_{31}+\alpha(\alpha+1) \mathrm{V}_{22}+\frac{5}{24} \alpha^{2} \mathrm{~V}_{04}\right] \tag{10.7}
\end{align*}
$$

$\operatorname{MSE}_{2}\left(\mathrm{t}_{2}^{\prime}\right)=\overline{\mathrm{Y}}^{2}\left[\mathrm{~V}_{20}+\mathrm{g}^{2} \beta^{2} \mathrm{~V}_{02}-2 \beta \mathrm{gV} \mathrm{V}_{11}-\beta^{3} \mathrm{~g}^{2}(\mathrm{~g}+1) \mathrm{V}_{03}+\mathrm{g}(3 \mathrm{~g}+1) \beta^{2} \mathrm{~V}_{12}\right.$
$-2 \beta g V_{21}-\left\{\frac{7 g^{3}+9 g^{2}+2 g}{3}\right\} \beta^{3} V_{31}+g(2 g+1) \beta^{2} V_{22}$

$$
\begin{equation*}
\left.+\left\{\frac{2 g^{3}+9 g^{2}+10 g+3}{6}\right\} \beta^{4} V_{04}\right] \tag{10.8}
\end{equation*}
$$

$$
\begin{align*}
\operatorname{MSE}_{2}\left(t_{3}^{\prime}\right)=\bar{Y}^{2} & {\left[V_{20}+w^{2} V_{02}-2 w V_{11}-w^{2}(w-1) V_{03}+w(w+1) V_{12}-2 w V_{21}\right.} \\
& \left.+\left\{\frac{5 w^{3}-3 w^{2}-2 w}{3}\right\} V_{31}+w V_{22}+\left\{\frac{7 w^{4}-18 w^{3}+11 w^{2}}{24}\right\} V_{04}\right] \tag{10.9}
\end{align*}
$$

$$
\begin{align*}
\operatorname{MSE}_{2}\left(t_{4}^{\prime}\right)=\bar{Y}^{2} & {\left[V_{20}+D^{2} V_{02}-2 D V_{11}-4 D_{1} V_{03}+\left(2 b D+2 D_{1}+2 D^{2}\right) V_{12}-2 D V_{21}\right.} \\
& +\left\{2 D^{2}+2 b^{2} D+2 D_{1}+4 b D_{1}+4 b D^{2}\right\} V_{31}+\left\{D^{2}+2 D_{1}+2 b D\right\} V_{22} \\
& \left.+\left\{3 b^{2} D^{2}+D_{1}^{2}+2 D_{2}+12 b D_{1}\right\} V_{04}\right\} \tag{10.10}
\end{align*}
$$

$\operatorname{MSE}_{2}\left(\mathrm{t}_{5}^{\prime}\right)=\overline{\mathrm{Y}}^{2} \mid \mathrm{V}_{20}+\mathrm{k}^{2} \mathrm{~V}_{02}-2 \mathrm{kV} \mathrm{V}_{11}+\mathrm{kV} \mathrm{V}_{12}-2 \mathrm{kV} \mathrm{V}_{21}+\mathrm{k}^{2}(\mathrm{k}-1) \mathrm{V}_{03}$

$$
\begin{equation*}
\left.+2 k^{2}(k-1) V_{31}+k V_{22}+\frac{\left(k^{2}-k\right)^{2}}{4} V_{04}\right] \tag{10.11}
\end{equation*}
$$

## 11. Numerical Illustration

For the natural population data, we shall calculate the bias and the mean square error of the estimator and compare Bias and MSE for the first and second order of approximation.

## Data Set-1

To illustrate the performance of above estimators, we have considered the natural Data given in Singh and Chaudhary (1986, p.162).

The data were collected in a pilot survey for estimating the extent of cultivation and production of fresh fruits in three districts of Uttar- Pradesh in the year 1976-1977.

Table 11.1: Biases and MSE's of the estimators

| Estimator | Bias |  | MSE |  |
| :---: | :---: | :---: | :---: | :---: |
|  | First order | Second order | First order | second order |
| $t_{1}^{\prime}$ | -10.82707903 | -13.65734654 | 1299.110219 | 1372.906438 |
| $t_{2}^{\prime}$ | -10.82707903 | 6.543275811 | 1299.110219 | 1367.548263 |
| $t_{3}^{\prime}$ | -27.05776113 | -27.0653128 | 1299.110219 | 1417.2785 |
| $t_{4}^{\prime}$ | 11.69553975 | -41.84516913 | 1299.110219 | 2605.736045 |
| $\mathrm{t}_{5}^{\prime}$ | -22.38574093 | -14.95110301 | 1299.110219 | 2440.644397 |

From Table 11.1 we observe that the MSE's of the estimators $\mathrm{t}_{1}^{\prime}, \mathrm{t}_{2}^{\prime}, \mathrm{t}_{3}^{\prime}, \mathrm{t}_{4}^{\prime}$ and $\mathrm{t}_{5}^{\prime}$ are same up to the first order of approximation but the biases are different. The MSE of the estimator $t_{2}^{\prime}$ is minimum under second order of approximation followed by the estimator $t_{1}^{\prime}$ and other estimators.

## Conclusion

In this study we have considered some estimators whose MSE's are same up to the first order of approximation. We have extended the study to second order of approximation to search for best estimator in the sense of minimum variance. The properties of the estimators are studied under SRSWOR and stratified random sampling. We have observed from Table 6.1 and Table 11.1 that the behavior of the estimators changes dramatically when we consider the terms up to second order of approximation.

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