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# Unbiased ratio estimators of the mean in stratified ranked set sampling

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### Abstract

Stratified ranked set sampling ( $S_t$ RSS) combines the advantages of stratification and ranked set sampling (RSS). In this paper, we propose several unbiased ratio type estimators using  $S_t$ RSS, when population mean of the auxiliary variable is known. The variances of the proposed unbiased ratio-type estimators are obtained to first degree of approximation. In simulation study the proposed estimators are more efficient as compared to other competitor estimators using Percentage Relative Efficiency (*PRE*), Percentage Relative Bias (*PRB*) and Percentage Relative Root Mean Square Error (*PRRMSE*).

**Keywords:** Stratified ranked set sampling, ratio estimators, relative efficiency. 2000 AMS Classification: 62D05

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### 1. Introduction

The method of ranked set sampling (RSS) was first introduced by McIntyre [12] as a cost efficient alternative to simple random sampling (SRS) method for those situations where measurement of the units are expensive or difficult to obtain but ranking of units according to the variable of interest is relatively simple and cheap. Section 2 describes RSS design. Takahasi and Wakimoto [21] have provided the necessary mathematical theory of RSS and have showed that the sample mean under RSS is an unbiased estimator of the finite population mean, and is more precise than the sample mean estimator under SRS.

Several population parameters, namely, coefficient of variation  $(C_x)$ , coefficient of kurtosis  $(\beta_{2x})$ , coefficient of correlation  $(\rho)$  etc., play a significant role, when they are

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known, in the estimation of the finite population mean (see Kadilar and Cingi [5, 6, 7], Kadilar et al. [8] and Upadhyaya and Singh [22]).

Stratified ranked set sampling  $(S_tRSS)$  was suggested by Samawi and Muttlak [16] to obtain more efficient estimators for population mean. Using  $S_tRSS$ , the performances of the combined and separate ratio estimators was obtained by Samawi and Siam [17]. Mandowara and Mehta [11] have used the idea of  $S_tRSS$  to obtain efficient ratio-type estimators. Singh et al. [20] have proposed ratio and product type efficient estimators for population mean under  $S_tRSS$ .

Hartley and Ross [4] were the first to propose an unbiased ratio-type estimator for finite population mean in SRS. Later on, Pascual [14] proposed an unbiased ratio type estimator in stratified random sampling. Singh et al. [19] and Kadilar and Cekim [9] suggested Hartley-Ross type unbiased estimators of finite population mean using the auxiliary information, such as the population coefficient of variation ( $C_x$ ), coefficient of kurtosis ( $\beta_{2x}$ ) and the coefficient of correlation ( $\rho$ ) in SRS. Recently Khan and Shabbir [10] suggested a class of Hartely-Ross type unbiased estimators in RSS. In this paper, we investigate the properties of separate ratio type estimator of the finite population mean based on  $S_t RSS$ .

### 2. Sampling scheme

According to McIntyre [12], we first choose a small number m as a set size such that one can easily rank the m elements of the population with sufficient accuracy. Let Yand X be study and the auxiliary variables. Then randomly select  $m^2$  bivariate sample units from the population and allocate them into m sets, each of size m. Then each sample is ranked with respect to one of the variables Y or X. Here, we assume that the perfect ranking is done on basis of the auxiliary variable X while the ranking of Y is with possible error. An actual measurement from the first sample is then taken on the unit with the smallest rank of X, together with variable Y associated with smallest rank of X. From second sample of size m, the variable Y associated with the second smallest rank of X is measured. The process is continued until the Y value associated with the highest rank of X is measured from the mth sample. This completes one cycle of the sampling. The process is repeated for r cycles to obtain the desired sample of size n = mr units. Thus in a RSS scheme, a total of  $m^2r$  units have been drawn from the population and only mr of them are selected for analysis.

In stratified ranked set sampling (see Samawi and Muttlak [16]), first choose  $m_h$ independent random samples from the *h*th stratum of the population, each of size  $m_h$ (h = 1, 2, ..., L). Rank the observations in each sample and use RSS procedure to get Lindependent RSS samples, each of size  $m_h$ , to get  $m_1 + m_2 + ... + m_L = m$  observations. This completes one cycle of  $S_t RSS$ . The whole process is repeated r times to get the desired sample size n = mr. To estimate population mean  $(\bar{Y})$  in  $S_t RSS$  using a ratio estimator, the procedure can be summarized as follows:

- Step 1: Select  $m_h^2$  bivariate sample units randomly from the  $h^{th}$  stratum of the population.
- Step 2: Arrange these selected units randomly into  $m_h$  sets, each of size  $m_h$ .
- Step 3: The procedure of ranked set sampling (RSS) is then applied on each of the sets to obtain the  $m_h$  sets of ranked set samples, each of size  $m_h$ . Here ranking is done with respect to the auxiliary variable X. These ranked set samples are collected together to form  $m_h$  sets, each of size  $m_h$  units.
- Step 4: Repeat the above steps r times for each stratum to get the desired sample of size  $n_h = m_h r$ .

For the  $j^{th}$  cycle and the  $h^{th}$  stratum, the  $S_t RSS$  is denoted by  $(Y_{h[1:m_h]j}, X_{h(1:m_h)j})$ ,  $(Y_{h[2:m_h]j}, X_{h(2:m_h)j}), \ldots, (Y_{h[mh:m_h]j}, X_{h(mh:m_h)j}), (j = 1, 2, \ldots, r)$  and  $h = 1, 2, \ldots, L$ . Here  $Y_{h[i:m_h]j}$  and  $X_{h[i:m_h]j}$  are the  $i^{th}$  ranked units in the  $i^{th}$  sample at the  $j^{th}$  cycle of the  $h^{th}$  stratum for the study and the auxiliary variables respectively.

Under  $S_t RSS$  scheme, the estimator  $\bar{y}_{S_t RSS}$ , is given by

(2.1) 
$$\bar{y}_{S_tRSS} = \sum_{h=1}^{L} P_h \bar{y}_{h[rss]}$$

where  $\bar{y}_{h[rss]} = (1/m_h r) \sum_{j=1}^r \sum_{i=1}^{m_h} y_{h[i:m_h]j}$  and  $P_h = N_h/N$  is the known *h*th stratum weight. Also,  $N_h$  is the *h*th stratum size and N is the population size. The variance of  $\bar{y}_{S_tRSS}$ , is given by

(2.2) 
$$V(\bar{y}_{S_tRSS}) = \sum_{h=1}^{L} P_h^2 \bar{Y}_h^2 \left( \gamma_h C_{y_h}^2 - W_{y_h}^2 \right),$$

where  $\gamma_h = (\frac{1}{m_h r})$ ,  $C_{y_h}$  is the coefficient of variation of  $Y_h$ ,  $W_{y_h}^2 = \frac{1}{m_h^2 r \bar{Y}_h^2} \sum_{i=1}^{m_h} \tau_{y_h[i:m_h]}^2$ , where  $\tau_{y_h[i:m_h]} = (\mu_{y_h[i:m_h]} - \bar{Y}_h)$  and  $\mu_{y_h[i:m_h]}$  is an order statistic from some specific distribution.

The aim of this paper is to estimate the population mean  $(\bar{Y})$  of a variable of interest under  $S_t RSS$ . To estimate the population mean, we proposed the following class of ratio-type estimators.

## 3. Proposed class of unbiased ratio estimators in $S_t RSS$

Consider a separate ratio estimator

$$(3.1) \quad \bar{y}_{LJ(k)} = \sum_{h=1}^{L} P_h \bar{r}_{h[rss]}^{(k)} \bar{X}_h^{(k)}, k = 1, 2, \dots, 9$$
where  $\bar{r}_{h[rss]}^{(k)} = \frac{\sum_{j=1}^{r} \sum_{i=1}^{m_h} r_{h[i:m_h]j}^{(k)}}{m_h r}, r_{h[i:m_h]j}^{(k)} = \frac{y_{h[i:m_h]j}}{x_{h(i:m_h)j}^{(k)}}, \bar{R}_h^{(k)} = E(\bar{r}_{h[rss]}^{(k)}),$ 

$$x_{h(i:m_h)j}^{(1)} = x_{h(i:m_h)j}, \bar{X}_h^{(1)} = \bar{X}_h, x_{h(i:m_h)j}^{(2)} = x_{h(i:m_h)j} + C_{x_h}, \bar{X}_h^{(2)} = \bar{X}_h + C_{x_h},$$

$$x_{h(i:m_h)j}^{(3)} = x_{h(i:m_h)j} + \beta_{2(x_h)}, \bar{X}_h^{(3)} = \bar{X}_h + \beta_{2(x_h)}, x_{h(i:m_h)j}^{(4)} = x_{h(i:m_h)j}\beta_{2(x_h)} + C_{x_h},$$

$$\bar{X}_h^{(4)} = \bar{X}_h\beta_{2(x_h)} + C_{x_h}, x_{h(i:m_h)j}^{(5)} = x_{h(i:m_h)j}C_{x_h} + \beta_{2(x_h)}, \bar{X}_h^{(5)} = \bar{X}_hC_{x_h} + \beta_{2(x_h)},$$

$$\bar{X}_h^{(6)} = x_{h(i:m_h)j}C_{x_h} + \rho_h, \bar{X}_h^{(6)} = \bar{X}_h + C_{x_h} + \rho_h, x_{h(i:m_h)j}^{(7)} = x_{h(i:m_h)j}\rho_h + C_{x_h},$$

$$\bar{X}_h^{(7)} = \bar{X}_h\rho_h + C_{x_h}, x_{h(i:m_h)j}^{(8)} = x_{h(i:m_h)j}\beta_{2(x_h)} + \rho_h, \bar{X}_h^{(8)} = \bar{X}_h\beta_{2(x_h)} + \rho_h, x_{h(i:m_h)j}^{(9)} = x_{h(i:m_h)j}\rho_h + \beta_{2(x_h)}, \bar{X}_h^{(9)} = \bar{X}_h\rho_h + \beta_{2(x_h)}, \text{for each estimator. Here, } \rho_h \text{ is the coefficient of variation and } \beta_{2(x_h)} \text{ is the coefficient of kurtosis of the auxiliary variable for the hth stratum.$$
The bias of  $\bar{y}_{LJ(k)}$ , is given by

$$B(\bar{y}_{LJ(k)}) = -\sum_{h=1}^{L} \left[ P_h \frac{(N_h - 1)}{N_h} S_{r_{h[i:m_h]}^{(k)} x_{h(i:m_h)}^{(k)}} \right], \ k = 1, 2, \dots, 9$$
  
where  $S_{r_{h[i:m_h]}^{(k)} x_{h(i:m_h)}^{(k)}} = \frac{1}{N_h - 1} \sum_{j=1}^{N_h} (r_{h[i:m_h]j}^{(k)} - \bar{R}_h^{(k)}) (x_{h(i:m_h)j}^{(k)} - \bar{X}_h^{(k)}).$ 

#### 3.1. Theorem. An unbiased estimator of

$$S_{r_{h[i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)}} = \frac{1}{N_{h}-1}\sum_{j=1}^{N_{h}} (r_{h[i:m_{h}]j}^{(k)} - \bar{R}_{h}^{(k)})(x_{h(i:m_{h})j}^{(k)} - \bar{X}_{h}^{(k)})$$

is given by

$$s_{r_{h[i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)}} = \frac{n_{h}}{n_{h}-1} (\bar{y}_{h[i:m_{h}]} - \bar{r}_{h(i:m_{h})}^{(k)} \bar{x}_{h(i:m_{h})}^{(k)}).$$

*Proof.* We have to prove that  $E(s_{r_{h[i:m_h]}^{(k)}x_{h(i:m_h)}^{(k)}}) = S_{r_{[i:m_h]}^{(k)}x_{h(i:m_h)}^{(k)}}$ . For fixed  $i, j = 1, 2, ..., n_h, r_{h[i:m_h]j}^{(k)}$  and  $x_{h(i:m_h)j}^{(k)}$  are simple random samples of size  $n_h$ .

$$\begin{split} & E(s_{r_{h[i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)}}) = E\left[\frac{n_{h}}{n_{h}-1}(\bar{y}_{h[i:m_{h}]} - \bar{r}_{h(i:m_{h})}^{(k)}\bar{x}_{h(i:m_{h})}^{(k)})\right], \\ &= E\left[\frac{1}{n_{h}-1}\sum_{j=1}^{n_{h}}(r_{h[i:m_{h}]j}^{(k)} - \bar{r}_{h[i:m_{h}]}^{(k)})(x_{h(i:m_{h})j}^{(k)} - \bar{x}_{h(i:m_{h})}^{(k)})\right], \\ &= \frac{1}{n_{h}-1}E\left[\sum_{j=1}^{n_{h}}r_{h[i:m_{h}]j}^{(k)}x_{h(i:m_{h})j}^{(k)} - n_{h}\bar{r}_{h[i:m_{h}]}^{(k)}\bar{x}_{h(i:m_{h})}^{(k)}\right], \\ &= \frac{1}{n_{h}-1}\left[\sum_{j=1}^{n_{h}}E(r_{h[i:m_{h}]j}^{(k)}x_{h(i:m_{h})j}^{(k)}) - n_{h}E(\bar{r}_{h[i:m_{h}]}^{(k)}\bar{x}_{h(i:m_{h})}^{(k)})\right], \\ &= \frac{1}{n_{h}-1}\left[\frac{n_{h}}{N_{h}}\sum_{j=1}^{N_{h}}r_{h[i:m_{h}]j}^{(k)}x_{h(i:m_{h})j}^{(k)} - n_{h}\left(Cov(\bar{r}_{h[i:m_{h}]}^{(k)}, \bar{x}_{h(i:m_{h})}^{(k)}) + \bar{R}_{h}^{(k)}\bar{X}_{h}^{(k)}\right)\right] \\ &= \frac{n_{h}}{n_{h}-1}\left[\frac{1}{N_{h}}\sum_{j=1}^{N_{h}}r_{h[i:m_{h}]j}^{(k)}x_{h(i:m_{h})j}^{(k)} - \bar{R}^{(k)}\bar{X}^{(k)} - \frac{S_{r_{[i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)}}{n_{h}}\right], \\ &= \frac{n_{h}}{n_{h}-1}\left(S_{r_{h[i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)} - \frac{S_{r_{h[i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)}}{n_{h}}\right), \\ &= S_{r_{h(i:m_{h}]}^{(k)}x_{h(i:m_{h})}^{(k)}}. \end{split}$$

So bias of  $\bar{y}_{LJ(k)}$  can be estimated by

(3.2) 
$$\hat{B}(\bar{y}_{LK(k)}) = -\sum_{h=1}^{L} P_h \left[ \frac{n_h(N_h - 1)}{N_h(n_h - 1)} (\bar{y}_{h[i:m_h]} - \bar{r}_{h(i)}^{(k)} \bar{x}_{h(i:m_h)}^{(k)}) \right], \quad k = 1, 2, \dots, 9.$$

Thus, a class of unbiased ratio-type estimators of population mean based on  $S_t RSS$  is

,

$$(3.3) \qquad \bar{y}_{LJ(k)}^{(u)} = \sum_{h=1}^{L} P_h \left[ \bar{r}_{h[i:m_h]}^{(k)} \bar{X}_h^{(k)} + \frac{n_h(N_h - 1)}{N_h(n_h - 1)} \left( \bar{y}_{h[i:m_h]} - \bar{r}_{h[i:m_h]}^{(k)} \bar{x}_{h(i:m_h)}^{(k)} \right) \right]$$

where k = 1, 2, ..., 9.

where k = 1, 2, ..., 9. To find the variances of the proposed unbiased estimators, we define the following notations: Let  $\bar{y}_{h[i:m_h]} = \bar{Y}_h(1 + \delta_{0h}), \bar{x}_{h(i:m_h)}^{(k)} = \bar{X}_h^{(k)}(1 + \delta_{1h}), \bar{r}_{h(i)}^{(k)} = \bar{R}_h^{(k)}(1 + \delta_{2h}),$ such that  $E(\delta_{ph}) = 0$ , (p = 0, 1, 2), (h = 1, 2, ..., L) and  $E(\delta_{0h}^2) = \gamma_h C_{y_h}^2 - W_{y_h}^2, E(\delta_{1h}^2) = \gamma_h C_{x_h^{(k)}}^2 - W_{x_h^{(k)}}^2,$   $E(\delta_{0h}\delta_{1h}) = \gamma_h C_{y_h x_h^{(k)}} - W_{y_h x_h^{(k)}}, E(\delta_{1h}\delta_{2h}) = \gamma_h C_{r_h^{(k)} x_h^{(k)}} - W_{r_h^{(k)} x_h^{(k)}},$ where where

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$$\begin{split} W_{y_h}^2 &= \frac{1}{m_h^2 r \bar{X}_h^2} \sum_{i=1}^{m_h} \tau_{y_h[i:m_h]}^2, W_{y_h x_h^{(k)}} = \frac{1}{m_h^2 r \bar{X}_h^{(k)} \bar{Y}_h} \sum_{i=1}^{m_h} \tau_{y_h x_h^{(k)}(i:m_h)}, \\ W_{x_h^{(k)}}^2 &= \frac{1}{m_h^2 r \bar{X}_h^{(k)} 2} \sum_{i=1}^{m_h} \tau_{x_h^{(k)}(i)}^2, \quad W_{r_h^{(k)} x_h^{(k)}} = \frac{1}{m_h^2 r \bar{X}_h^{(k)} \bar{R}_h^{(k)}} \sum_{i=1}^{m_h} \tau_{r_h^{(k)} x_h^{(k)}(i:m_h)}, \\ \tau_{y_h[i:m_h]} &= (\mu_{y_h[i:m_h]} - \bar{Y}_h), \quad \tau_{x_h^{(k)}(i:m_h)} = (\mu_{x_h^{(k)}(i:m_h)} - \bar{X}_h^{(k)}), \\ \tau_{y_h x_h^{(k)}(i:m_h)} &= (\mu_{y_h[i:m_h]} - \bar{Y}_h)(\mu_{x_h^{(k)}(i:m_h)} - \bar{X}_h^{(k)}) \text{ and } \\ \tau_{r_h^{(k)} x_h^{(k)}(i:m_h)} &= (\mu_{r_h^{(k)}(i:m_h)} - \bar{R}_h^{(k)})(\mu_{x_h^{(k)}(i:m_h)} - \bar{X}_h^{(k)}). \\ & \text{Here, } C_{y_h x_h^{(k)}} &= \rho C_{y_h} C_{x_h^{(k)}}, \text{ where } C_{y_h} \text{ and } C_{x^{(k)}} \text{ are the coefficients of variation of } \end{split}$$

 $Y_h$  and  $X_h^{(k)}$  respectively. Also  $\bar{Y}_h$  and  $\bar{X}_h^{(k)}$  are the population means of  $Y_h$  and  $X_h^{(k)}$  respectively. The values of  $\mu_{y_h[i:m_h]}$  and  $\mu_{x_h^{(k)}(i:m_h)}$  depend on order statistic from some specific distributions (see Arnold et al.[1]). In terms of  $\delta's$ , we get

 $\bar{y}_{LJ(k)}^{(u)} = \sum_{h=1}^{L} P_h \Big[ \bar{X}_h^{(k)} \bar{R}_h^{(k)}(1+\delta_{2h}) + \frac{n_h(N_h-1)}{N_h(n_h-1)} \{ \bar{Y}_h(1+\delta_{0h}) - \bar{X}_h^{(k)} \bar{R}_h^{(k)}(1+\delta_{1h})(1+\delta_{2h}) \} \Big].$ Assuming  $\frac{n_h(N_h-1)}{N_h(n_h-1)} \cong 1$  and considering first order approximation, we get

$$(\bar{y}_{LJ(k)}^{(u)} - \bar{Y}) \cong \sum_{h=1}^{L} P_h \left[ (\bar{Y}_h \delta_{0h} - \bar{X}_h^{(k)} \bar{R}_h^{(k)} \delta_{1h}) \right].$$

Taking square and then expectation, the variance of  $\bar{y}_{LJ(k)}^{(u)}$ , is given by

$$V(\bar{y}_{LJ(k)}^{(u)}) \cong \sum_{h=1}^{L} P_h^2 \left[ \bar{Y}_h^2(\gamma_h C_{yh}^2 - W_{yh}^2) + \bar{X}_h^{(k)2} \bar{R}_h^{(k)2}(\gamma_h C_{xh^{(k)}}^2 - W_{xh^{(k)}}^2) \right] (3.4) \qquad - \sum_{h=1}^{L} P_h^2 \left[ 2\bar{R}_h^{(k)} \bar{X}_h^{(k)} \bar{Y}_h(\gamma_h C_{yhxh^{(k)}} - W_{yhxh^{(k)}}) \right], k = 1, 2, \dots, 9.$$

### 4. Simulation study

To compare the performances of the proposed estimators, a simulation study is conducted. Ranking is performed on basis of the auxiliary variable X. Bivariate random observations  $(X_h, Y_h)$ , h = 1, 2, ..., L were generated from a bivariate gamma population with correlation parameter  $\rho_{yxh}$ . Using 20,000 simulations, estimates of variances for unbiased ratio-type estimators are computed under stratified ranked sampling scheme as described in Section 2. Estimators are compared in terms of percentage relative efficiencies (*PREs*).

The simulation results show that with decrease in correlation coefficients  $\rho_{yxh}$ , *PREs* decrease, as expected. The numerical values given in the first five rows are obtained by assuming equal correlations across the strata, whereas the last three rows assume unequal correlations across the strata. The simulation results are presented in Table 1. We use the following expression to obtain the *PRE*:

$$PRE_{(k)} = \frac{V(\bar{y}_{(S_tRSS)})}{V(\bar{y}_{LJ(k)}^{(u)})} \times 100, \quad k = 1, 2, \dots, 9.$$

The expression of variance is as follows:

$$V(\bar{y}_P) = \frac{1}{20000} \sum_{i=1}^{20000} (\bar{y}_P - \bar{Y})^2, \ P = \bar{y}_{(S_t RSS)}, \bar{y}_{LJ(k)}^{(u)}.$$

The simulation study is completed with some alternative empirical measures, such as the relative bias (RB) and the relative root mean square error (RRMSE), which are used to compare the precision of different estimators. The values of RB allow us to analyze the

empirical bias of the different estimators, whereas the values of RRMSE reveal the most efficient estimator from an empirical point of view. Chambers and Dunstan [2], Rao et al. [15], Silva and Skinner [18], Harms and Duchesne [3] and Munoz and Rueda [13] used RB and RRMSE. We define percentage relative bias (PRB) and percentage relative root mean square error (PRRMSE) as

$$PRB_{(k)} = \frac{1}{\bar{Y}} \left[ \frac{1}{20000} \sum_{i=1}^{20000} \left( \bar{y}_{LJ(k)i} - \bar{Y} \right) \right] \times 100, \quad k = 1, 2, \dots, 9.$$

and

$$PRRMSE_{(k)} = \frac{1}{\bar{Y}} \left[ \frac{1}{20000} \sum_{i=1}^{20000} \left( \bar{y}_{LJ(k)i} - \bar{Y} \right)^2 \right]^{\frac{1}{2}} \times 100, \quad k = 1, 2, \dots, 9.$$

Here  $\bar{Y}$  is the parameter of interest and  $\bar{y}_{LJ(k)i}$  is the value of  $\hat{Y}$  for the *i*th simulated sample. The values of *PRB* and *PRRMSE* are presented in Tables 2 and 3 respectively. The simulation results indicate that for a given sample size n = mr, *PRB* decreases with increase in correlation coefficient. Among all estimators,  $\bar{y}_{LJ(3)}$  has minimum absolute *PRB* and *PRRMSE*.

Table 1. Percentage Relative Efficiencies PREs for separate ratiotype estimators for the simulated data, obtained through bivariate gamma distribution.

L = 3,	$P_h = (.30, .30, .40), \ m_h = (3, 4, 5), \ r = 5 \ n_h = (.40, .40), \ r = (.40, $								15, 20, 25).		
$ ho_{yxh}$	$PRE_{(1)}$	$PRE_{(2)}$	$PRE_{(3)}$	$PRE_{(4)}$	$PRE_{(5)}$	$PRE_{(6)}$	$PRE_{(7)}$	$PRE_{(8)}$	$PRE_{(9)}$		
0.90, 0.90, 0.90	120.7	137.5	242.9	127.2	123.0	144.5	140.2	130.1	130.4		
$0.80,\; 0.80,\; 0.80$	115.7	130.9	231.8	121.6	120.8	138.8	133.9	124.3	127.5		
$0.70,\ 0.70,\ 0.70$	113.4	125.2	221.8	116.8	118.8	133.9	128.4	119.2	124.7		
$0.60,\ 0.60,\ 0.60$	106.6	119.3	209.8	114.5	116.8	128.9	122.8	113.8	121.9		
0.50, 0.50, 0.50	102.2	113.7	198.5	106.6	114.7	123.9	117.5	108.7	119.1		
0.90, 0.80, 0.70	113.8	128.6	226.9	119.6	119.5	136.8	131.7	122.1	125.4		
$0.80,\ 0.70,\ 0.60$	110.1	123.5	217.2	115.3	117.5	132.1	126.9	117.6	122.8		
$0.70,\ 0.60,\ 0.50$	105.4	117.5	206.9	110.1	115.3	126.5	121.2	112.2	119.7		

### 5. Conclusion

It is observed from the simulation results (see Table 1) that the proposed unbiased ratio type estimators  $\bar{y}_{LJ(k)}$ , (k = 1, 2, ..., 9), have high *PRE* in comparison to  $\bar{y}_{(S_tRSS)}$ . Also, the values of *PRE* decreases with decrease in correlation. The simulation result of Table 2 indicates that the proposed ratio-type estimators have reasonable biases, since the values of *PRB* are all less than 2.2% in absolute terms. Also, for a given sample size, *PRB* decreases with increase in correlation coefficient. Among all estimators,  $\bar{y}_{LJ(3)}$ is more efficient as compared to the other considered estimators. So, we conclude that the proposed unbiased ratio-type estimators are preferable over  $\bar{y}_{(S_tRSS)}$  under  $S_tRSS$ 

Table 2. Percentage Relative Bias (PRB) of the different estimators.

,					( ' ' ' '	/				
$ ho_{yxh}$	$\bar{y}_{StRSS}$	$\bar{y}_{LJ(1)}$	$\bar{y}_{LJ(2)}$	$\bar{y}_{LJ(3)}$	$\bar{y}_{LJ(4)}$	$\bar{y}_{LJ(5)}$	$\bar{y}_{LJ(6)}$	$\bar{y}_{LJ(7)}$	$\bar{y}_{LJ(8)}$	$\bar{y}_{LJ(9)}$
0.90, 0.90, 0.90	2.02	1.01	1.99	-0.35	2.01	1.38	1.79	1.97	2.00	1.53
0.80, 0.80, 0.80	2.05	1.02	2.02	-0.33	2.04	1.39	1.79	1.98	2.02	1.53
0.70, 0.70, 0.70	2.08	1.04	2.04	-0.32	2.07	1.40	1.82	2.01	2.06	1.54
0.60, 0.60, 0.60	2.13	1.07	2.08	-0.31	2.12	1.41	1.84	2.03	2.10	1.55
0.50, 0.50, 0.50	2.14	1.08	2.08	-0.30	2.12	1.39	1.85	2.03	2.11	1.57
0.90, 0.80, 0.70	2.05	1.03	2.03	-0.33	2.04	1.36	1.81	1.99	2.03	1.51
0.80, 0.70, 0.60	2.09	1.04	2.06	-0.31	2.08	1.38	1.82	2.00	2.07	1.54
0.70, 0.60, 0.50	2.18	1.14	2.14	-0.31	2.17	1.47	1.92	2.09	2.16	1.61

L = 3,  $P_h = (.30, .30, .40)$ ,  $m_h = (3, 4, 5)$ , r = 5  $n_h = (15, 20, 25)$ .

**Table 3.** Percentage Relative Root Mean Squarer Error (PRRMSE)of the different estimators.

L = 3,	$P_h = (.30, .30, .40), \ m_h = (3, 4, 5), \ r = 5 \ n_h = (15, 20, 25).$									
$ ho_{yxh}$	$\bar{y}_{StRSS}$	$\bar{y}_{LJ(1)}$	$\bar{y}_{LJ(2)}$	$\bar{y}_{LJ(3)}$	$\bar{y}_{LJ(4)}$	$\bar{y}_{LJ(5)}$	$\bar{y}_{LJ(6)}$	$\bar{y}_{LJ(7)}$	$\bar{y}_{LJ(8)}$	$\bar{y}_{LJ(9)}$
0.90, 0.90, 0.90	4.91	4.79	4.66	3.53	4.81	4.63	4.47	4.61	4.76	4.56
$0.80, \ 0.80, \ 0.80$	4.90	4.76	4.66	3.37	4.81	4.52	4.44	4.60	4.76	4.48
$0.70, \ 0.70, \ 0.70$	4.89	4.66	4.66	3.27	4.80	4.44	4.42	4.59	4.75	4.41
$0.60, \ 0.60, \ 0.60$	4.88	4.53	4.66	3.16	4.79	4.35	4.39	4.57	4.75	4.34
$0.50, \ 0.50, \ 0.50$	4.84	4.38	4.63	3.05	4.76	4.26	4.35	4.54	4.72	4.25
0.90, 0.80, 0.70	4.87	4.77	4.66	3.36	4.79	4.51	4.42	4.58	4.75	4.46
$0.80, \ 0.70, \ 0.60$	4.86	4.56	4.64	3.17	4.78	4.39	4.41	4.58	4.73	4.37
$0.70, \ 0.60, \ 0.50$	4.85	4.52	4.63	3.15	4.76	4.35	4.38	4.55	4.72	4.33

scheme.

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### References

- Arnold, B. C., Balakrishnan, N. and Nagaraja, H. N. A First Course in Order Statistics, Vol. 54, Siam, 1992.
- [2] Chambers, R.L. and Dunstan, R. Estimating the distribution function from survey data, Biometrika, 73, 597-604, 1986.

- [3] Harms, T and Duchesne, P. On calibration estimation for quantile, Survey Methodology, 32, 37-52, 2006.
- [4] Hartley, H.O. and Ross, A. Unbiased ratio estimators, Nature, 174, 270-271, 1954.
- [5] Kadilar, C and Cingi, H. A new ratio estimator in stratified random sampling, Communication in Statistics: Theory and Methods, 34, 597-602, 2005.
- [6] Kadilar, C and Cingi, H. New ratio estimators using correlation coefficient, Interstat, 1-11, 2006.
- [7] Kadilar, C and Cingi, H. An improvement in estimating the population mean by using the correlation coefficient, Hacettepe Journal of Mathematics and Statistics, 35 (1), 103-109, 2006.
- [8] Kadilar, C, Candan, M. and Cingi, H. Ratio estimators using robust regression, Hacettepe Journal of Mathematics and Statistics, 36 (2), 181-188, 2007.
- Kadilar, C and Cekim, H.O. Hartley-Ross type estimators in simple random sampling, Proceedings of the International Conference on Numerical Analysis and Applied Mathematics, AIP Conf.Proc. 1648, 610007-1-610007-4; Doi:10.1063/1.4912849, 2014.
- [10] Khan, L. and Shabbir, J. A class of Hartley-Ross type unbiased estimators for population mean using ranked set sampling, Hacettepe Journal of Mathematics and Statistics, Doi:10.15672/HJMS.20156210579, 2015.
- [11] Mandowara, V. L. and Mehta, N. Modified ratio estimators using stratified ranked set sampling, Hacettepe Journal of Mathematics and Statistics, 43 (3), 461-471, 2014.
- [12] McIntyre, G. A method for unbiased selective sampling using ranked sets, Crop and Pasture Science, 3 (4), 385-390, 1952.
- [13] Munoz, J. F. and Rueda, M. New imputation method for missing data using quantiles, Journal of Computational and Applied Mathematics, 232, 305-317, 2009.
- [14] Pascual, J. N. Unbiased ratio estimators in stratified sampling, Journal of the American Statistical Association, 293 (56), 70-87, 1961.
- [15] Rao, J.N.K. Kovar, J.G. and Mantel, H.J. On estimating distribution function and quantiles from survey data using auxiliary information, Biometrika, 77, 365-375, 1990.
- [16] Samawi, H. M. and Muttlak, H. A. Estimation of ratio using ranked set sampling, Biometrical Journal, 38 (6), 753-764, 1996.
- [17] Samawi, H. M. and Siam, M.I. Ratio estimation using stratified ranked set sample, Metron, 61 (1), 75-90, 2003.
- [18] Silva, P.L.D. and Skinner, C.J. Estimating distribution function with auxiliary information using poststratification, Journal of Official Statistics, 11, 277-294, 1995.
- [19] Singh, H. P., Sharma, B. and Tailor, R. Hartley-Ross type estimators for population mean using known parameters of auxiliary variate, Communications in Statistics-Theory and Methods, 43 (3), 547-565, 2014.
- [20] Singh, H. P., Mehta, V. and Pal, S.K. Dual to ratio and product type estimators using stratified ranked set sampling, Journal of Basic and Applied Engineering Research, 1 (13), 7-12, 2014.
- [21] Takahasi, K. and Wakimoto, K. On unbiased estimates of the population mean based on the sample stratified by means of ordering, Annals of the Institute of Statistical Mathematics, 20 (1), 1-31, 1968.
- [22] Upadhyaya, L. N. and Singh, H. P. Use of transformed auxiliary variable in estimating the finite population mean, Biometrical Journal, 41 (5), 627-636, 1999.