Stallion Journal for Multidisciplinary Associated Research Studies
ISSN (Online): 2583-3340
Volume-4 Issue-5 || October 2025 || PP. 94-101 https://doi.org/10.55544/sjmars.4.5.14

A Ratio Type Exponential Estimator for Estimating Finite Population Mean in Double Sampling for Stratification

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www.sjmars.com || Vol. 4 No. 5 (2025): October Issue

Date of Submission: 11-10-2025	**Date of Acceptance:** 26-10-2025	**Date of Publication:** 30-10-2025

ABSTRACT

In this paper, we proposed a ratio type exponential estimator for estimating the finite population mean in double sampling for stratification. The bias and mean square error of the proposed estimator are obtained. The proposed estimators have been compared with usual unbiased estimator, Ige Tripathi (1987), Tailor et al. (2014) estimators in double sampling for stratification. The proposed estimator is found to perform better than usual unbiased estimator, Ige Tripathi (1987), Tailor et al. (2014) estimators in double sampling for stratification. To judge the performance of the proposed estimator an empirical study has been carried out.

Keywords- Auxiliary Variable, Stratified Sampling, Double Sampling, Bias, MSE.

MSC: 62D05

I. INTRODUCTION

Use of auxiliary information in the estimation of population parameters such as population mean, ratio of two population means, coefficient of variation etc. has been in practice. Ratio, product and regression methods of estimation are good examples in this context. Cochran (1940) initiated the use of auxiliary information at estimation stage and proposed ratio estimator for population mean. It is well established fact that ratio type estimator provide better efficiency in comparison to simple mean estimator if the study variate and auxiliary variate are positively correlated.

Hansen et al. (1946) proposed a combined ratio estimator for population mean in stratified random sampling. Later Kadilar and Cingi (2003) and Singh and Vishwakarma (2006) discussed some ratio and product type estimators using known parameters of auxiliary variate for estimation of population mean in stratified random sampling. Bahl and Tuteja (1991) pioneered ratio and type exponential estimators using an exponential function in simple random sampling.

Usually, heterogeneous populations are encountered in practice. In such a situation, stratification is extensively used procedure in sample surveys to provide samples that are representatives of major sub-groups of a population. When the sampling frame within strata is known, stratified sampling is used, but there are many situations of practical importance where strata weights are known but a frame within the strata is not available. For example in household survey in a city, number of households in different colonies may be available, but list of households may not be available. In such a situation post-stratification is used. However, in other situations with the passage of time, the stratum weights may not be available exactly as they become out-of-date. Further, the information on the stratification variable may not be readily available but could be made available by diverting a part of the survey budget to its collection.

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This type of situation occurs during the household surveys, when the investigator does not have information about newly added households in different colonies. This situation leads investigator to use double sampling for stratification which was developed by Neyman (1938). For more studies on this topic the reader is referred to the papers by Rao (1973), Ige and Tripathi (1987, 1991), Singh and Vishwakarma (2007), Vishwakarma and Singh (2012), Tailor et al. (2014), Tailor and Lone (2014), Vishwakarma and Zeeshan (2018) and Singh and Nigam (2020 a, b), Clement, E. P. (2021). Recently, Singh, H.P., Nigam, P. (2022) worked for the estimation of finite population mean in Double Sampling for Stratification.
Following Shabbir and Gupta (2011) and Tailor et al. (2014), we proposed a ratio type exponential estimator for estimating the finite population mean in double sampling for stratification.

II. PROCEDURE, NOTATIONS AND DEFINITIONS:

Consider a finite population $U = \{U_1, U_2 \ldots\ldots\ldots U_N\}$having N distinct and identifiable unit partioned into L Strata. Let y and x be the study and auxiliary variate, respectively. Let $\bar{Y}$ be the population mean of the study variate$y$. suppose we want to estimate the population mean $\bar{Y}$ of y and consider it desirable to stratify the population on the basis of the values of an auxiliary variate x but the frequency distribution of xis unknown. Let the population of size N be stratified in to L strata of size N_h with strata weight $W_h = \frac{N_h}{N}$, $(h = 1,2, \ldots. L)$ when strata weight are unknown, double sampling for stratification is used. It consist the following steps. [see Rao(1973) and Ige and Tripathi (1987)].
(a) A first phase sample S of size $n'$is drawn using simple random sampling without replacement and only auxiliary variate x is observed.
(b) The sample S is stratified in to L strata on the basis of auxiliary variable x. Let n'_h be the number of units in h^{th} stratum $(h = 1,2..L)$ such that $\sum_{h=1}^{L} n'_h = n'$.
(c) From each n'_h unnits, a sample of size $n_h = v_h n'_h$ is drawn where 0<v_h<1is the predetermined probability of selecting a sample of size n_h from strata of size n'_h and it constitutes a sample S of size $n = \sum_{h=1}^{L} n_h$. In sample S' both study variate y and auxiliary variate x are observed.
Let y and x be the study variate and auxiliary variate respectively. Then we define
$\sum_{h=1}^{L} n_h = n.$ Size of the sample S'
$W_h = \frac{N_h}{N}$
$\bar{y}_h = \frac{1}{n_h}\sum_{i=1}^{n_h} \bar{y}_{hi}$: Mean of the second phase sample taken from h^{th} stratum for the study variate y.
$\bar{x}_h = \frac{1}{n_h}\sum_{i=1}^{n_h} \bar{x}_{hi}$: Mean of the second phase sample taken from h^{th} stratum for the auxiliry variate x.
$\bar{x}'_h = \frac{1}{n'_h}\sum_{i=1}^{n'_h} x_{hi}$ h^{th} First phase sample mean of the h^{th} stratum for the auxiliary variate x
$\bar{Y}_h = \frac{1}{N_h}\sum_{i=1}^{N_h} y_{hi}$ h^{th} stratum mean for the study variate y.
$\bar{X}_h = \frac{1}{N_h}\sum_{i=1}^{N_h} x_{hi}$ h^{th} stratum mean for the auxiliary variate x.
$S^2{}_y = \frac{1}{N-1}\sum_{h=1}^{L}\sum_{i=1}^{N_h}(y_{hi} - \bar{Y})^2$; Population mean square of the study variate y.
$S^2{}_x = \frac{1}{N-1}\sum_{h=1}^{L}\sum_{i=1}^{N_h}(x_{hi} - \bar{X}_h)^2$: Population mean square of the auxiliary variate$x$.
$S^2{}_{yh} = \frac{1}{N_h-1}\sum_{i=1}^{N_h}(y_{hi} - \bar{Y}_h)^2$: h^{th} Stratum mean square of the study variate y.
$S^2{}_{xh} = \frac{1}{N_h-1}\sum_{i=1}^{N_h}(x_{hi} - \bar{X}_h)^2$: h^{th} Stratum mean square of the auxiliary variate x.
$S_{yxh} = \frac{1}{N_h-1}\sum_{i=1}^{N_h}(x_{hi} - \bar{X}_h)(y_{hi} - \bar{Y}_h)$ Covariance between y *and* x.
$C^2{}_{xh} = \frac{S^2{}_{xh}}{\bar{X}^2}$, $C^2{}_{yh} = \frac{S^2{}_{yh}}{\bar{Y}^2}$ be the coefficient of variation of h^{th} stratum.
$C_{hxy} = \rho_h C_{hy} C_{hx}$, ρ_h*is* The correlation coefficient between y *and* x
$\bar{y}_{ds} = \sum_{h=1}^{L} W_h \bar{y}_h$: Unbiased estimator of population mean $\bar{Y}$ in second phase or double sampling mean of the study variate y.
$\bar{x}_{ds} = \sum_{h=1}^{L} W_h \bar{x}_h$: Unbiased estimator of population mean $\bar{X}$ in second phase or double sampling mean of the auxiliary variate x.
$\bar{x}' = \sum_{h=1}^{L} W_h \bar{x}_h{}'$:
$f = \frac{n'}{N}$: First phase sampling fraction.
To obtain the bias and MSE of the suggested estimator, we define
$\bar{y}_{ds} = \bar{Y}(1 + e_0)$, $\bar{x}_{ds} = \bar{X}(1 + e_1)$ And $\bar{x}' = \bar{X}(1 + e_1{}')$
$E(e_0) = E(e_1) = E(e'_1) = 0$
$E(e_0^2) = \frac{1}{\bar{Y}^2}V(\bar{y}_{ds}) = \frac{1}{\bar{Y}^2}\left[S_y^2\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h} - 1\right)S_{hy}^2\right]$

$E(e_1^2) = \frac{1}{\bar{X}^2} V(\bar{y}_{ds}) = \frac{1}{\bar{X}^2}\left[S_x^2\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)S_{hx}^2\right]$

$E(e'^2_1) = \frac{1}{\bar{X}^2}\left[S_x^2\left(\frac{1-f}{n'}\right)\right]$

$E(e_0 e_1) = \frac{1}{\bar{Y}\bar{X}} cov(\bar{y}_{ds}, \bar{x}_{ds}) = \frac{1}{\bar{Y}\bar{X}}\left[S_{xy}\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)S_{xyh}\right]$

$E(e_0 e'_1) = \frac{1}{\bar{Y}\bar{X}}\left[S_{xy}\left(\frac{1-f}{n'}\right)\right]$

$E(e_1 e'_1) = \frac{1}{\bar{X}^2}\left[S_x^2\left(\frac{1-f}{n'}\right)\right]$

Let $A = \frac{1}{\bar{Y}^2} S_y^2\left(\frac{1-f}{n'}\right), B = \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)S_{hy}^2, C = \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)S_{hx}^2,$

$D = \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)S_{hxy}, E = S_x^2\left(\frac{1-f}{n'}\right), F = S_{xy}\left(\frac{1-f}{n'}\right)$

We have reviewed only those estimators from which our proposed estimator would be better.

III. REVIEW OF SOME EXISTING ESTIMATORS:

The usual unbiased estimator for population mean $\bar{Y}$ is defined by

$$\bar{y}_{ds} = \sum_{h=1}^{L} w_h \bar{y}_h \quad (3.1)$$

The variance /MSE of $\bar{y}_{ds}$ is given by

$$V(\bar{y}_{ds}) = MSE(\bar{y}_{ds}) = \left[S_y^2\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)S_{hy}^2\right] \quad (3.2)$$

Ige and Tripathi (1987) defined classical ratio estimator in double sampling for stratification as

$$d_R = \bar{y}_{ds}\frac{\bar{x}'}{\bar{x}_{ds}} \quad (3.3)$$

$$B(d_R) = \frac{1}{\bar{X}}\left[\sum_{h=1}^{L}\frac{W_h}{n'}\left(\frac{1}{v_h}-1\right)\{R_1 S_{yh}^2 - S_{yxh}\}\right] \quad (3.4)$$

$$MSE(d_R) = S_y^2\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)\left[S^2{}_{yh} + R_1^2 S_{xh}^2 - 2R_1 S_{yxh}\right] \quad (3.5)$$

Tailor et al. (2014) Estimator

$$d_{Re} = \bar{y}_{ds} exp\left[\frac{\bar{x}' - \bar{x}_{ds}}{\bar{x}' + \bar{x}_{ds}}\right] \quad (3.6)$$

$$B(d_{Re}) = \frac{1}{8\bar{X}}\left[3S_{yx}\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)\left(3S_{xh}^2 - S_{yxh}\right)\right] \quad (3.7)$$

$$MSE(d_{Re}) = S_y^2\left(\frac{1-f}{n'}\right) + \frac{1}{n'}\sum_{h=1}^{L} W_h\left(\frac{1}{v_h}-1\right)\left(S^2{}_{yh} + \frac{R_1^2}{4}S_{xh}^2 - \frac{1}{4}R_1 S_{yxh}\right) \quad (3.8)$$

We have reviewed only those estimators from which our proposed estimator would be better.

IV. PROPOSED ESTIMATOR

Following Shabbir and Gupta (2011) and Tailor et al. (2014), we proposed a ratio type exponential estimator for estimating the finite population mean in double sampling for stratification.

$$d_{Pe} = \bar{y}_{ds}\left[\theta\left(\frac{\bar{x}'}{\bar{x}_{ds}}\right) + (1-\theta)\left(\frac{\bar{x}_{ds}}{\bar{x}'}\right)\right] exp\left[\frac{\bar{x}' - \bar{x}_{ds}}{\bar{x}' + \bar{x}_{ds}}\right] \quad (4.1)$$

Where θ is a constant whose value determined later and expressing the proposed estimator d_{Pe} in terms of e's we have

$$d_{Pe} = \bar{Y}(1+e_0)\left[\theta\frac{\bar{X}(1+e_1')}{\bar{X}(1+e_1)} + (1-\theta)\frac{\bar{X}(1+e_1)}{\bar{X}(1+e_1')}\right] exp\left[\frac{\bar{X}(1+e_1') - \bar{X}(1+e_1)}{\bar{X}(1+e_1') + \bar{X}(1+e_1)}\right]$$

$$d_{Pe} = \bar{Y}(1+e_0)[\theta(1+e_1')(1+e_1)^{-1}(1-\theta)(1+e_1)(1+e_1')^{-1}]exp[(e_1'-e_1)((2+e_1'+e_1)^{-1})]$$

$$d_{Pe} = \bar{Y}(1+e_0)\left[\theta(1+e_1')\left(1-e_1+\frac{e_1^2}{2}-\cdots\right)(1-\theta)(1+e_1)\left(1-e_1'+\frac{e_1'^2}{2}-\cdots\right)\right] exp\left[(e_1'-e_1)\frac{1}{2}\left(1+\frac{e_1'+e_1}{2}\right)^{-1}\right]$$

$$d_{Pe} = \bar{Y}(1+e_0)\left[\theta\left(-2e_1+\frac{e_1^2}{2}+2e_1'-\frac{e_1'^2}{2}\right) + \left(1-e_1'+\frac{e_1'^2}{2}+e_1+e_1e_1'+\right)\right] exp\left[(e_1'-e_1)\frac{1}{2}\left(1-\frac{e_1'+e_1}{2}+\frac{(e_1'+e_1)^2}{4}+\cdots\right)\right]$$

$$d_{Pe} = \bar{Y}(1+e_0)\left[1+e_1(-2\theta+1)+e_1'(2\theta-1)+\frac{e_1^2}{2}\theta+\frac{e_1'^2}{2}(-\theta+1)+e_1e_1'+\right] exp\left[\frac{(e_1'-e_1)}{2}-\frac{e_1'^2-e_1^2}{4}+\frac{(e_1'+e_1)^2(e_1'-e_1)}{8}+\cdots\right]$$

$$d_{Pe} = \bar{Y}(1+e_0)\left[1+e_1(-2\theta+1)+e_1'(2\theta-1)+\frac{e_1^2}{2}\theta+\frac{e_1'^2}{2}(-\theta+1)+e_1e_1'+\right] exp\frac{(e_1'-e_1)}{2}\, exp\frac{(e_1'^2-e_1^2)}{4}\, exp\frac{(e_1'+e_1)^2(e_1'-e_1)}{8}$$

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$$d_{Pe} = \bar{Y}(1+e_0)\left[1+e_1(-2\theta+1)+e_1'(2\theta-1)+\frac{e_1^2}{2}\theta+\frac{e_1'^2}{2}(-\theta+1)+e_1e_1'+\frac{e_1e_1'^2}{2}\right]\left[1+\frac{(e_1'-e_1)}{2}+\frac{(e_1'-e_1)^2}{8}+\cdots\right]\left[1+\frac{(e_1'^2-e_1^2)}{4}+\cdots\right]$$

$$d_{Pe} = \bar{Y}(1+e_0)\left[1+e_1(-2\theta+1)+e_1'(2\theta-1)+\frac{e_1^2}{2}\theta+\frac{e_1'^2}{2}(-\theta+1)+e_1e_1'+\frac{e_1e_1'^2}{2}\right]\left[1+\frac{(e_1'^2-e_1^2)}{4}+\frac{(e_1'-e_1)}{2}+\frac{(e_1'-e_1)^2}{8}+\cdots\right]$$

$$d_{Pe} = \bar{Y}\left[1-e_1\frac{(4\theta-1)}{2}+e_1'\frac{(4\theta-1)}{2}+\frac{e_1'^2}{2}\frac{(4\theta+3)}{4}+\frac{e_1^2}{2}\frac{(12\theta-5)}{4}+e_1e_1'\frac{(4\theta+3)}{4}+e_0-e_0e_1\frac{(4\theta-1)}{2}+e_0e_1'\frac{(4\theta-1)}{2}\right]$$

Keeping terms only up to order two in e's, we get

$$d_{Pe}-\bar{Y} = \bar{Y}\left[-e_1\frac{(4\theta-1)}{2}+e_1'\frac{(4\theta-1)}{2}+\frac{e_1^2}{2}\frac{(12\theta-5)}{4}+\frac{e_1'^2}{2}\frac{(4\theta+3)}{4}+e_1e_1'\frac{(4\theta+3)}{4}+e_0-e_0e_1\frac{(4\theta-1)}{2}+e_0e_1'\frac{(4\theta-1)}{2}\right] \quad (4.2)$$

Taking expectation both side of equation (4.2) and neglecting the higher order term

$$E(d_{Pe}-\bar{Y}) = \bar{Y}E\left[-e_1\frac{(4\theta-1)}{2}+e_1'\frac{(4\theta-1)}{2}+\frac{e_1^2}{2}\frac{(12\theta-5)}{4}+\frac{e_1'^2}{2}\frac{(4\theta+3)}{4}+e_1e_1'\frac{(4\theta+3)}{4}+e_0-e_0e_1\frac{(4\theta-1)}{2}+e_0e_1'\frac{(4\theta-1)}{2}\right]$$

$$B(d_{Pe}) = \bar{Y}\left[\frac{(6\theta+1)}{2}\left\{C_x^2\left(\frac{1-f}{n'}\right)\right\}+\frac{(12\theta-5)}{8}\left\{\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)C_{hx}^2\right\}+\frac{(4\theta-1)}{2}\left\{\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)C_{hyx}\right\}\right] \quad (4.3)$$

On squaring both side of equation (4.2) and neglecting the higher order term

$$(d_{Pe}-\bar{Y})^2 = \bar{Y}^2\left[-e_1\frac{(4\theta-1)}{2}+e_1'\frac{(4\theta-1)}{2}+\frac{e_1^2}{2}\frac{(12\theta-5)}{4}+\frac{e_1'^2}{2}\frac{(4\theta+3)}{4}+e_1e_1'\frac{(4\theta+3)}{4}+e_0-e_0e_1\frac{(4\theta-1)}{2}+e_0e_1'\frac{(4\theta-1)}{2}\right]^2$$

$$(d_{Pe}-\bar{Y})^2 = \bar{Y}^2\left[e_0^2+e_1^2\left(\frac{4\theta-1}{2}\right)^2+e_1'^2\left(\frac{4\theta-1}{2}\right)^2-2e_0e_1\frac{(4\theta-1)}{2}-2e_1'e_1\left(\frac{4\theta-1}{2}\right)^2+2e_0e_1'\frac{(4\theta-1)}{2}\right]$$

$$MSE(d_{Pe}) = \bar{Y}^2\left[\frac{1}{\bar{Y}^2}S_y^2\left(\frac{1-f}{n'}\right)+\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hy}^2}{\bar{Y}^2}+\left(\frac{4\theta-1}{2}\right)^2\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hx}^2}{\bar{X}^2}-(4\theta-1)\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hyx}}{\bar{X}\bar{Y}}\right] \quad (4.4)$$

Differentiate equation (4.4) w.r.to θ for obtaining the optimum value of θ.

$$\theta = \frac{1}{4}\left[\frac{2\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hyx}}{\bar{X}\bar{Y}}}{\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hx}^2}{\bar{X}^2}}+1\right]$$

Substituting the value of θ in (4.4) we get minimum MSE of d_{pe} is given by

$$MSE(d_{Pe})min = \bar{Y}^2\left[\frac{1}{\bar{Y}^2}S_y^2\left(\frac{1-f}{n'}\right)+\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hy}^2}{\bar{Y}^2}-\frac{1}{n'}\frac{\left(\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hyx}}{\bar{X}\bar{Y}}\right)^2}{\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hx}^2}{\bar{X}^2}}\right] \quad (4.5)$$

V. THEORETICAL EFFICIENCY COMPARISON

In this section the proposed stratified exponential ratio estimator in double sampling were compared theoretically with other existing estimator.

(1) The MSE of proposed ratio estimator (d_{Pe}) is better than sample mean per unit estimator $(\bar{y}_{ds})$ if

$$MSE(\bar{y}_{ds})-MSE(d_{Pe})_{min} > 0$$

$$\bar{Y}^2\left[\frac{1}{\bar{Y}^2}S_y^2\left(\frac{1-f}{n'}\right)+\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hy}^2}{\bar{Y}^2}\right]-\bar{Y}^2\left[\frac{1}{\bar{Y}^2}S_y^2\left(\frac{1-f}{n'}\right)+\frac{1}{n'}\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hy}^2}{\bar{Y}^2}-\frac{1}{n'}\frac{\left(\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hyx}}{\bar{X}\bar{Y}}\right)^2}{\sum_{h=1}^{L}W_h\left(\frac{1}{v_h}-1\right)\frac{S_{hx}^2}{\bar{X}^2}}\right] > 0$$

$$\frac{D^2}{C} > 0 \quad (5.1)$$

(2) The MSE of proposed estimator (d_{Pe}) is better than The MSE of Ige and Tripathi estimator (d_R) if

$$MSE(\mathrm{d_R})-MSE(d_{Pe})_{min} > 0$$

$$R_1^2C+\frac{D^2}{C} > 2R_1D \quad (5.2)$$

(3) The MSE of proposed estimator (d_{Pe}) is better than The MSE of Tailor et. al (2014) Estimator (d_{Re}) if

$$MSE(\mathrm{d_{Re}})-MSE(d_{Pe})_{min} > 0$$

$$\frac{R_1^2}{4}C + \frac{D^2}{C} > \frac{R_1}{4}D \tag{5.3}$$

Expression (5.1), (5.2), (5.3) shows the condition in which proposed estimator performs better than usual unbiased estimator, Ige and Tripathi, Tailor et al. estimators.

VI. EMPIRICAL STUDY

To judge the performance of the proposed estimator in comparison to other existing estimators, two population data sets are being considered. The parametric value of population is given below

Source of Data: Tailor et al. (2014)
Parametric value of population 1
x: Production in '000 Tons and y:Productivity (MT/ Hectare)

Stratum	n_h	n'_h	N_h	$\bar{Y}_h$	$\bar{X}_h$	s_{yh}	S_{xh}	S_{yxh}	S_y^2
1	2	4	10	1.70	10.41	0.50	3.53	1.61	2.21
2	2	4	10	3.67	289.14	1.41	111.61	144.88	

Source of Data: Singh, H.P. and Nigam, P. (2022)
Parametric value of population 2
x:Area in Hectare, y:Productivity (MT/ Hectare)

Stratum	n_h	n'_h	N_h	$\bar{Y}_h$	$\bar{X}_h$	s_{yh}	S_{xh}	S_{yxh}	S_y^2
1	4	7	10	142.80	1632	6.09	102.17	-239.30	528.43
2	4	7	10	102.60	2036	12.60	103.46	-655.30	

Table: MSE, PRE of $(\bar{y}_{ds})$, (d_R), (d_{Re}), (d_{Pe}) with respect to $(\bar{y}_{ds})$

Estimator	**Population 1st**		**Population 2nd**	
	MSE	PRE	MSE	PRE
$\bar{y}_{ds}$	0.3056	100	11.7195	100
d_R	0.3049	100.23	11.7168	100.02
d_{Re}	0.2998	104.37	11.7164	100.03
d_{Pe}	**0.198**	**154.2**	**10.49**	**111.72**

For Comparison of different estimators we calculate percent relative efficiency (PRE) of $(\bar{y}_{ds})$, (d_R), (d_{Re}), (d_{Pe}) with respect to $(\bar{y}_{ds})$ as

$$PRE(d_R, \bar{y}_{ds}) = \frac{V(\bar{y}_{ds})}{MSE\ (d_R)} \times 100$$

$$PRE(d_{Re}, \bar{y}_{ds}) = \frac{V(\bar{y}_{ds})}{MSE\ (d_{Re})} \times 100$$

$$PRE(d_{Pe}, \bar{y}_{ds}) = \frac{V(\bar{y}_{ds})}{MSE\ (d_{Pe})} \times 100$$

Table 1 gives the MSE, Percent Relative Efficiency of estimators $(\bar{y}_{ds})$, (d_R), (d_{Re}), (d_{Pe}) with respect to usual unbiased estimator $(\bar{y}_{ds})$. it observe for Population 1st PRE of usual unbiased estimator $(\bar{y}_{ds})$ is 100 and PRE of Ige Tripathi estimator (d_R) is 100.23, PRE of Tailor et al. (d_{Re}), estimator is 104.37 and the PRE of proposed ratio type exponential estimator is 154.2 which is highest. Also in case of Population 2nd, the PRE of proposed estimator is 111.72. PRE of both populations is highest in comparison of other existing estimators.

VII. SIMULATION STUDY

To see the performance of existing and proposed estimator in double sampling for stratification we have carried out a simulation study. We generate an artificial population of size $N = 1500$ and divided in to 5 strata. $N_h(h = 1,2 \ldots..5)$ as 100, 200, 300, 400, 500, we assume $X's$ distribution are chi square with 5 degree of freedom and Gamma distribution with shape parameter as 2.3 and scale parameter as 1.five strata were formed according to increasing value of X.

The study variable Y generated using $Y_{hi} = \beta X_{hi} + \varepsilon_{hi,}\ \ i = 1,2 \ldots.N_h$ where the random effects ε_{hi} generated from normal distribution with parameter $N(0,2)$, we choose $\beta = 2.5$. At first phase samples are selected by SRSWOR from each strata of sizes $\acute{n}_1 = 20, \acute{n}_2 = 40, \acute{n}_3 = 60, \acute{n}_4 = 80, \acute{n}_5 = 100$ and at second phase samples are selected in each strata from the samples drawn at first phase by SRSWOR of sizes $n_1 = 10, n_2 = 20, n_3 = 30, n_4 = 40, n_5 = 50$. The above experiment as repeated 500 times using R Software and the MSE and PRE of the estimators are computed through these iterations using the formula:

$MSE(\hat{Y}_i) = \frac{\sum_{i=1}^{500}(\hat{Y}_i - \bar{Y})^2}{500}$ Where $\hat{Y}_i = \bar{y}_{ds},\ d_R, d_{Re}, d_{Pe}$

$PRE(\hat{Y}_i) = \frac{MSE(\bar{y}_{ds})}{MSE(d_i)} \times 100$, Where $d_i = d_R, d_{Re}, d_{Pe}$

Table: (7.1) MSE, PRE of $(\bar{y}_{ds})$, $(d_R), (d_{Re}), (d_{Pe})$ with respect to $(\bar{y}_{ds})$

Estimator	MSE	PRE
$\bar{y}_{ds}$	12.96	100
d_R	5.99	216.36
d_{Re}	9.25	140.10
d_{Pe}	5.94	218.18

Table (7.1) shows that PRE of proposed estimator is more efficient in comparison of other existing estimators.

VIII. CONCLUSION

Section (5) provides the conditions under which the proposed estimator (d_{Pe}) performs better than usual unbiased estimator$(\bar{y}_{ds})$, Ige and Tripathi (d_R), Tailor et al. (d_{Re}) estimators. In Section 6, empirical study reveals that the proposed ratio type exponential estimator (d_p) has minimum MSE and maximum PRE in comparison the other existing estimators for population 1, 2. In Section 7, simulation study shows that the proposed ratio type exponential estimator (d_p) has minimum MSE and maximum PRE in comparison the other existing estimators for artificial population.

All comparison shows that the proposed estimator(d_{Pe}) is more efficient than usual unbiased estimator $(\bar{y}_{ds})$, Ige and Tripathi (d_R), Tailor et al. (d_{Re}) estimators.

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APPENDIX

```
install.packages("readxl")
library(readxl)
h<-5;N<-1500
N1<-100;N2<-200;N3<-300;N4<-400;N5<-500
n1<-10;n2<-20;n3<-30;n4<-40;n5<-50
n<-150
n1f<-20;n2f<-40;n3f<-60;n4f<-80;n5f<-100
nf<-300
W1<-N1/N;W2<-N2/N;W3<-N3/N;W4<-N4/N;W5<-N5/N
f<-nf/N
del1<-1;del2<-1;del3<-1;del4<-1;del5<-1
x <- rchisq(n = 1500, df = 5)
e<-rnorm(1500,0,2)
beta<-2.5
y<-beta*x+e
df<-cbind(y,x)
#df[,2]
head(df)
df1<-df[order(df[,2]),]
newdata<-data.frame(df1,g=c(rep(1,100),rep(2,200),rep(3,300),rep(4,400),rep(5,500)))
dim(df1)
head(newdata)
X<-split(newdata,newdata$g)
y<-lapply(seq_along(X), function(x)as.data.frame(X[[x]])[,1:2])
head(y)
A1<-y[[1]]
A2<-y[[2]]
A3<-y[[3]]
A4<-y[[4]]
A5<-y[[5]]
sy<-sd(newdata$y)
X1<-mean(A1$x);X2<-mean(A2$x);X3<-mean(A3$x);X4<-mean(A4$x);X5<-mean(A5$x)
S1X<-sd(A1$x);S2X<-sd(A2$x);S3X<-sd(A3$x);S4X<-sd(A4$x);S5X<-sd(A5$x)
Cx1<-S1X/X1;Cx2<-S2X/X2;Cx3<-S3X/X3;Cx4<-S4X/X4;Cx5<-S5X/X5
y1<-mean(A1$y);y2<-mean(A2$y);y3<-mean(A3$y);y4<-mean(A4$y);y5<-mean(A5$y)
S1y<-sd(A1$y);S2y<-sd(A2$y);S3y<-sd(A3$y);S4y<-sd(A4$y);S5y<-sd(A5$y)
Mys<-W1*y1+W2*y2+W3*y3+W4*y4+W5*y5
Mxs<-W1*X1+W2*X2+W3*X3+W4*X4+W5*X5
S1XY<-cov(A1$x,A1$y);S2XY<-cov(A2$x,A2$y);S3XY<-cov(A3$x,A3$y);S4XY<-cov(A4$x,A4$y);S5XY<-
cov(A5$x,A5$y)
Cx1y1<-S1XY/Mys*Mxs;Cx2y2<-S2XY/Mys*Mxs;Cx3y3<-S3XY/Mys*Mxs;Cx4y4<-S4XY/Mys*Mxs;Cx5y5<-
S5XY/Mys*Mxs
r1<-cor(A1$x,A1$y);r2<-cor(A2$x,A2$y);r3<-cor(A3$x,A3$y);r4<-cor(A4$x,A4$y);r5<-cor(A5$x,A5$y)

mf1<-NA;mf2<-NA;mf3<-NA;mf4<-NA;mf5<-NA;ms1<-NA;ms2<-NA;ms3<-NA;ms4<-NA;ms5<-NA;
mf11<-NA;mf21<-NA;mf31<-NA;mf41<-NA;mf51<-NA;ms12<-NA;ms22<-NA;ms32<-NA;ms42<-NA;ms52<-NA;
```

Stallion Journal for Multidisciplinary Associated Research Studies
ISSN (Online): 2583-3340
Volume-4 Issue-5 || October 2025 || PP. 94-101 https://doi.org/10.55544/sjmars.4.5.14

```
mf11s<-NA;mf21s<-NA;mf31s<-NA;mf41s<-NA;mf51s<-NA;ms12s<-NA;ms22s<-NA;ms32s<-NA;ms42s<-
NA;ms52s<-NA;
ysds<-NA;xsds<-NA;xfds<-NA;dR<-NA;dRe<-NA;dpe<-NA
cv11<-NA;cv12<-NA;cv13<-NA;cv14<-NA;cv15<-NA;cvxy1<-NA;cvxy2<-NA;cvxy3<-NA
cv21<-NA;cv22<-NA;cv23<-NA;cv24<-NA;cv25<-NA;theeta<-NA
r11<-NA;r12<-NA;r13<-NA;r14<-NA;r15<-NA;cxy1<-NA;cxy2<-NA;cxy3<-NA;cxy4<-NA;cxy5<-NA;
mSE1<-NA;mSE2<-NA;mSE3<-NA;mSEt4<-NA;mSEt5<-NA;mSEt6<-NA;mSEt7<-NA;mSEt8<-NA;mSEt9<-
NA;mSEt10<-NA
mSEp<-NA
for(i in 1:500){
  samf<-sample(1:100,20,replace=F)
  saf<-A1[samf,]
  sam<-sample(1:20,10,replace=F)
  sas<-A1[sam,]
  samf1<-sample(1:200,40,replace=F)
  saf1<-A2[samf1,]
  sam1<-sample(1:40,20,replace=F)
  sas1<-A2[sam1,]
  samf2<-sample(1:300,60,replace=F)
  saf2<-A3[samf2,]
  sam2<-sample(1:60,30,replace=F)
  sas2<-A3[sam2,]
  samf3<-sample(1:400,80,replace=F)
  saf3<-A4[samf3,]
  sam3<-sample(1:80,40,replace=F)
  sas3<-A4[sam3,]
  samf4<-sample(1:500,100,replace=F)
  saf4<-A5[samf,]
  sam4<-sample(1:100,50,replace=F)
  sas4<-A5[sam,]
  mf1[i]<-mean(saf$y);mf2[i]<-mean(saf1$y);mf3[i]<-mean(saf2$y);mf4[i]<-mean(saf3$y);mf5[i]<-mean(saf4$y)
  ms1[i]<-mean(sas$y);ms2[i]<-mean(sas1$y);ms3[i]<-mean(sas2$y);ms4[i]<-mean(sas3$y);ms5[i]<-mean(sas4$y)
  mf11[i]<-mean(saf$x);mf21[i]<-mean(saf1$x);mf31[i]<-mean(saf2$x);mf41[i]<-mean(saf3$x);mf51[i]<-mean(saf4$x)
  ms12[i]<-mean(sas$x);ms22[i]<-mean(sas1$x);ms32[i]<-mean(sas2$x);ms42[i]<-mean(sas3$x);ms52[i]<-mean(sas4$x)
  mf11s[i]<-sd(saf$x);mf21s[i]<-sd(saf1$x);mf31s[i]<-sd(saf2$x);mf41s[i]<-sd(saf3$x);mf51s[i]<-sd(saf4$x)
  ms12s[i]<-sd(sas$x);ms22s[i]<-sd(sas1$x);ms32s[i]<-sd(sas2$x);ms42s[i]<-sd(sas3$x);ms52s[i]<-sd(sas4$x)
  r11[i]<-cor(saf$x,saf$y);r12[i]<-cor(saf1$x,saf1$y);r13[i]<-cor(saf2$x,saf2$y);r14[i]<-cor(saf3$x,saf3$y);r15[i]<-
cor(saf4$x,saf4$y)
  cv11[i]<- mf11s/mf11;cv12[i]<-mf21s/mf21;cv13[i]<-mf31s/mf31;cv14[i]<-mf41s/mf41;cv15[i]<-mf51s/mf51
  cv21[i]<-ms12s/ms12;cv22[i]<-ms22s/ms22;cv23[i]<-ms32s/ms32;cv24[i]<-ms42s/ms42;cv25[i]<-ms52s/ms52
  cxy1[i]<-cov(sas$x,sas$y);cxy2[i]<-cov(sas1$x,sas1$y);cxy3[i]<-cov(sas2$x,sas2$y);cxy4[i]<-
cov(sas3$x,sas3$y);cxy5[i]<-cov(sas4$x,sas4$y)
  theeta[i]<-
1/4*(2*(W1*del1*cxy1+W2*del2*cxy2+W3*del3*cxy3+W4*del4*cxy4+W5*del5*cxy5)/(W1*del1*cv21[i]^2+W2*del2
*cv22[i]^2+W3*del3*cv23[i]^2+W4*del4*cv24[i]+W5*del5*cv25[i])+1)
  ysds[i]<-W1*ms1[i]+W2*ms2[i]+W3*ms3[i]+W4*ms4[i]+W5*ms5[i]
  xfds[i]<-W1*mf11[i]+W2*mf21[i]+W3*mf31[i]+W4*mf41[i]+W5*mf51[i]
  xsds[i]<-W1*ms12[i]+W2*ms22[i]+W3*ms32[i]+W4*ms42[i]+W5*ms52[i]
  dR[i]<- ysds[i]*(xfds[i]/xsds[i])
  dRe[i]<-ysds[i]*(exp((xfds[i]-xsds[i])/(xfds[i]+xsds[i])))
  mSE1[i]<-(ysds[i]-Mys)^2;mSE2[i]<-(dR[i]-Mys)^2;mSE3[i]<-(dRe[i]-Mys)^2
 dpe[i]<-ysds[i]*((theeta*(xfds[i]/xsds[i])+(1-theeta)*(xsds[i]/xfds[i]))*(exp((xfds[i]-xsds[i])/(xfds[i]+xsds[i]))))
 mSEp[i]<-(dpe-Mys)^2
}
MSE1<-mean(mSE1);MSE2<-mean(mSE2);MSE3<-mean(mSE3)
MSEp<-mean(mSEp)
PRE2<-(MSE1/MSE2)*100;PRE3<-(MSE1/MSE3)*100;PREp<-(MSE1/MSEp)*100
```