Bol. Soc. Paran. Mat.
©SPM – E-ISSN-2175-1188
SPM: www.spm.uem.br/bspm

(3s.) **v. 2025 (43)** : 1–10.
ISSN-0037-8712
doi:10.5269/bspm.68413

Some New Efficient Linear Regression Ratio Type Estimators For Estimating The Population Mean In Sampling Theory

Vinay Kumar Yadav and Shakti Prasad

ABSTRACT: This article deals with some new efficient linear regression ratio type estimators for estimating the population mean in sampling theory by using the auxiliary information of quartile deviation and deciles. The proposed estimators can be considered an efficient extension to the work of Kadilar and Cingi (2004 & 2006) and Subzar et al. (2017). The theoretical results are derived, and a comparative study is conducted. The suggested estimators are shown to have smaller mean squared errors than the Kadilar and Cingi (2004 & 2006) and Subzar (2017) estimators. The percent relative efficiencies of the suggested estimators for various sample sizes are involved in simulation studies for a given natural population data set, and the results are found to be quite encouraging, providing an improvement over all previous work.

Key Words: Auxiliary information, Ratio estimator, Mean squared error (MSE), Percent Relative efficiency(RE(%)).

Contents

1. Introduction

In sampling theory one of the important objectives is to estimate the study variable with more precision. To gain these objective statisticians from last few decades are incorporating the auxiliary information and have been recognised that use of this information helps us to get improvement in the gain of precision. Ratio, product and regression estimators are good examples in the context. Cochran [1], Sisodia and Dwivedi [2], Upadhyaya and Singh [3], Yan and Tian [4], Subramani and Kumarapandian ([5], [6], [7] & [8]), Swain [9] and Abid et al.([10], [11] & [12]) etc. have considered ratio type estimators using the known values of an auxiliary variables in sampling theory.

Motivated by Subzar et al. [13], Prasad ([14], [15] & [16]), Koyuncu and Kadilar [17] and Searls [18], we have suggested some efficient linear regression ratio type estimators for estimating population mean $\bar{Y}$ by using quartile deviation and deciles of an auxiliary variable in sampling theory and have shown that the suggested estimators are superior than the other methods currently used for estimation in this work.

In the domain of sample surveys and statistical estimation, a series of interesting articles have been published over a period of several years. Beginning in 2011 with the work of Upadhyaya et al. [19], these articles include contributions from Subramani and Ajith [20], Singh et al. [21], Singh et al. [22], Yadav et al. [23], Zaman and Kadilar [24], Yadav and Zaman [25], Yadav and Prasad [26] and Prasad and Yadav [27]. Collectively, these publications have helped move the field forward by introducing diverse

Submitted May 31, 2023. Published September 29, 2023
2010 *Mathematics Subject Classification:* 62D05.

estimation techniques and enhancing the efficiency of ratio-type estimators for sample surveys.

Let x and y be denoted by the positively correlated auxiliary and study variables respectively. Let n units be the simple random sample (without replacement) are drawn from a finite population of N units to estimate population mean $\bar{Y}$ on the basis of a random sample. The consequently symbols have been describing as follows:

$\bar{X}$, $\bar{Y}$: Population means of variables x and y respectively.
$S_x^2 = (N-1)^{-1}\sum_{i=1}^{N}(x_i - \bar{X})^2$: Population variance of variable x.
S_y^2 : Population variance of variable y .
$S_{yx} = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{Y})(x_i - \bar{X})$: Population covariance between variables x and y.
C_x and C_y : Coefficients of variation of variables x and y respectively.
$\beta_1(x)$: Population coefficient of skewness of variable x .
$\beta_2(x)$: Population coefficient of kurtosis of variable x .
ρ : Correlation coefficient between variables x and y.
$D_i, i = 1, 2, ..., 10$: Population deciles of an auxiliary variable.
$QD = \frac{Q_3 - Q_1}{2}$: Population quartile deviation of an auxiliary variable.

The remaining parts of the manuscript are structured as follows: In Section 2, we offered a literature review of existing estimators. In Section 3, we offered the suggested estimators. In Section 4, we derive the efficiency comparison of various existing estimators with respect to proposed estimators. In Sections 5, we conducted simulation study, and in the last Sections, 6, we arrived at the conclusions.

2. Estimators in Literature:

Kadilar and Cingi ([28] and [29]) considered the following ratio type estimators for the population mean $\bar{Y}$ by using auxiliary variables in survey sampling:

$\bar{Y}_{KC(1)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}}\bar{X}$, $\bar{Y}_{KC(2)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}+C_x}(\bar{X}+C_x)$,
$\bar{Y}_{KC(3)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}+\beta_2(x)}(\bar{X}+\beta_2(x))$, $\bar{Y}_{KC(4)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}\beta_2(x)+C_x}(\bar{X}\beta_2(x)+C_x)$,
$\bar{Y}_{KC(5)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}C_x+\beta_2(x)}(\bar{X}C_x+\beta_2(x))$, $\bar{Y}_{KC(6)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}+\rho}(\bar{X}+\rho)$,
$\bar{Y}_{KC(7)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}C_x+\rho}(\bar{X}C_x+\rho)$, $\bar{Y}_{KC(8)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}\rho+C_x}(\bar{X}\rho+C_x)$,
$\bar{Y}_{KC(9)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}\beta_2(x)+\rho}(\bar{X}\beta_2(x)+\rho)$, $\bar{Y}_{KC(10)} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}\rho+\beta_2(x)}(\bar{X}\rho+\beta_2(x))$.

where $\hat{\beta} = \frac{s_{yx}}{s_x^2}$, $s_{yx} = \frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x})$, $s_x^2 = (n-1)^{-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$

The Mean squared errors of the estimators $\bar{Y}_{KC(i)}$ $(i = 1, 2, ..., 10)$ are drawn by

$$MSE(\bar{Y}_{KC(i)}) = \left(\frac{1}{n} - \frac{1}{N}\right)\left(KC_i^2C_x^2 + \left(1-\rho^2\right)C_y^2\right)\bar{Y}^2 \tag{2.1}$$

where $KC_1 = 1$, $KC_2 = \bar{X}/(\bar{X}+C_x)$, $KC_3 = \bar{X}/(\bar{X}+\beta_2(x))$, $KC_4 = \bar{X}\beta_2(x)/(\bar{X}\beta_2(x)+C_x)$, $KC_5 = C_x\bar{X}/(C_x\bar{X}+\beta_2(x))$, $KC_6 = \bar{X}/(\bar{X}+\rho)$, $KC_7 = \bar{X}C_x/(\bar{X}C_x+\rho)$, $KC_8 = \bar{X}\rho/(\bar{X}\rho+C_x)$, $KC_9 = \bar{X}\beta_2(x)/(\bar{X}\beta_2(x)+\rho)$, $KC_{10} = \rho\bar{X}/(\bar{X}\rho+\beta_2(x))$.

Subzar et al. [13] considered the following ratio type estimators using the quartile deviation and deciles of an auxiliary variables are as follows;

$\bar{Y}_{SU1} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_1)}(\bar{X}QD+D_1)$, $\bar{Y}_{SU2} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_2)}(\bar{X}QD+D_2)$,
$\bar{Y}_{SU3} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_3)}(\bar{X}QD+D_3)$, $\bar{Y}_{SU4} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_4)}(\bar{X}QD+D_4)$,
$\bar{Y}_{SU5} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_5)}(\bar{X}QD+D_5)$, $\bar{Y}_{SU6} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_6)}(\bar{X}QD+D_6)$,
$\bar{Y}_{SU7} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_7)}(\bar{X}QD+D_7)$, $\bar{Y}_{SU8} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_8)}(\bar{X}QD+D_8)$,
$\bar{Y}_{SU9} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_9)}(\bar{X}QD+D_9)$, $\bar{Y}_{SU10} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}QD+D_{10})}(\bar{X}QD+D_{10})$,
$\bar{Y}_{SU11} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_1+QD)}(\bar{X}D_1+QD)$, $\bar{Y}_{SU12} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_2+QD)}(\bar{X}D_2+QD)$,
$\bar{Y}_{SU13} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_3+QD)}(\bar{X}D_3+QD)$, $\bar{Y}_{SU14} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_4+QD)}(\bar{X}D_4+QD)$,

$\bar{Y}_{SU15} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_5+QD)}(\bar{X}D_5+QD)$, $\bar{Y}_{SU16} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_6+QD)}(\bar{X}D_6+QD)$,
$\bar{Y}_{SU17} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_7+QD)}(\bar{X}D_7+QD)$, $\bar{Y}_{SU18} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_8+QD)}(\bar{X}D_8+QD)$,
$\bar{Y}_{SU19} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_9+QD)}(\bar{X}D_9+QD)$, $\bar{Y}_{SU20} = \frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{(\bar{x}D_{10}+QD)}(\bar{X}D_{10}+QD)$.
The mean squared error of Subzar et al. [13] estimators are given by;

$$MSE(\bar{Y}_{SUi}) = \bar{Y}^2\left(\frac{1}{n}-\frac{1}{N}\right)\left(SU_i^2C_x^2+C_y^2(1-\rho^2)\right) \tag{2.2}$$

where $(i = 1,2,...,20)$ and $SU_1 = \frac{\bar{X}QD}{\bar{X}QD+D_1}$, $SU_2 = \frac{\bar{X}QD}{\bar{X}QD+D_2}$, $SU_3 = \frac{\bar{X}QD}{\bar{X}QD+D_3}$, $SU_4 = \frac{\bar{X}QD}{\bar{X}QD+D_4}$, $SU_5 = \frac{\bar{X}QD}{\bar{X}QD+D_5}$, $SU_6 = \frac{\bar{X}QD}{\bar{X}QD+D_6}$, $SU_7 = \frac{\bar{X}QD}{\bar{X}QD+D_7}$, $SU_8 = \frac{\bar{X}QD}{\bar{X}QD+D_8}$, $SU_9 = \frac{\bar{X}QD}{\bar{X}QD+D_9}$, $SU_{10} = \frac{\bar{X}QD}{\bar{X}QD+D_{10}}$, $SU_{11} = \frac{\bar{X}D_1}{\bar{X}D_1+QD}$, $SU_{12} = \frac{\bar{X}D_2}{\bar{X}D_2+QD}$, $SU_{13} = \frac{\bar{X}D_3}{\bar{X}D_3+QD}$, $SU_{14} = \frac{\bar{X}D_4}{\bar{X}D_4+QD}$, $SU_{15} = \frac{\bar{X}D_5}{\bar{X}D_5+QD}$, $SU_{16} = \frac{\bar{X}D_6}{\bar{X}D_6+QD}$, $SU_{17} = \frac{\bar{X}D_7}{\bar{X}D_7+QD}$, $SU_{18} = \frac{\bar{X}D_8}{\bar{X}D_8+QD}$, $SU_{19} = \frac{\bar{X}D_9}{\bar{X}D_9+QD}$, $SU_{20} = \frac{\bar{X}D_{10}}{\bar{X}D_{10}+QD}$.

3. Suggested Estimators

Motivated by Subzar et al. [13], Prasad ([14], [15] and [16]), Koyuncu & Kadilar [17] and Searls [18], we propose some efficient linear regression ratio type estimators $\bar{Y}_{PS(j)}$, $(j = 1,2,...,20)$ by using the known values of conventional location parameters of an auxiliary variables are as follows;
$\bar{Y}_{PS(1)} = k_1\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_1}(\bar{X}QD+D_1)$, $\bar{Y}_{PS(2)} = k_2\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_2}(\bar{X}QD+D_2)$
$\bar{Y}_{PS(3)} = k_3\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_3}(\bar{X}QD+D_3)$, $\bar{Y}_{PS(4)} = k_4\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_4}(\bar{X}QD+D_4)$
$\bar{Y}_{PS(5)} = k_5\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_5}(\bar{X}QD+D_5)$, $\bar{Y}_{PS(6)} = k_6\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_6}(\bar{X}QD+D_6)$
$\bar{Y}_{PS(7)} = k_7\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_7}(\bar{X}QD+D_7)$, $\bar{Y}_{PS(8)} = k_8\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_8}(\bar{X}QD+D_8)$
$\bar{Y}_{PS(9)} = k_9\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_9}(\bar{X}QD+D_9)$, $\bar{Y}_{PS(10)} = k_{10}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}QD+D_{10}}(\bar{X}QD+D_{10})$
$\bar{Y}_{PS(11)} = k_{11}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_1+QD}(\bar{X}D_1+QD)$, $\bar{Y}_{PS(12)} = k_{12}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_2+QD}(\bar{X}D_2+QD)$
$\bar{Y}_{PS(13)} = k_{13}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_3+QD}(\bar{X}D_3+QD)$, $\bar{Y}_{PS(14)} = k_{14}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_4+QD}(\bar{X}D_4+QD)$
$\bar{Y}_{PS(15)} = k_{15}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_5+QD}(\bar{X}D_5+QD)$, $\bar{Y}_{PS(16)} = k_{16}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_6+QD}(\bar{X}D_6+QD)$
$\bar{Y}_{PS(17)} = k_{17}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_7+QD}(\bar{X}D_7+QD)$, $\bar{Y}_{PS(18)} = k_{18}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_8+QD}(\bar{X}D_8+QD)$
$\bar{Y}_{PS(19)} = k_{19}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_9+QD}(\bar{X}D_9+QD)$, $\bar{Y}_{PS(20)} = k_{20}\frac{\bar{y}+\hat{\beta}(\bar{X}-\bar{x})}{\bar{x}D_{10}+QD}(\bar{X}D_{10}+QD)$
To obtain the equation of MSEs of suggested estimators, let us define $\bar{y} = \bar{Y}(1+\epsilon_0)$, $\bar{x} = \bar{X}(1+\epsilon_1)$, $s_{yx} = S_{yx}(1+\epsilon_2)$ and $s_x^2 = S_x^2(1+\epsilon_3)$ such that $E(\epsilon_j) = 0$, $|\epsilon_j| < 1 \forall\ j = 0,1,2,3$.
Under the above transformations, the MSE of these estimators $\bar{Y}_{PS(j)}$, $(j = 1,2,...,20)$ are as follows:

$$MSE(\bar{Y}_{PS(j)}) = E\left(\bar{Y}_{PS(j)}-\bar{Y}\right)^2 = (k_j-1)^2\bar{Y}^2 + \left(\frac{1}{n}-\frac{1}{N}\right)k_j^2\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right)\bar{Y}^2 \tag{3.1}$$

The equations of the MSEs of the proposed estimators $\bar{Y}_{PS(j)}$, $(j = 1,2,...,20)$ are minimized for the optimum values of k_j are obtain by

$$k_j^* = \frac{1}{1+\left(\frac{1}{n}-\frac{1}{N}\right)\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right)} \tag{3.2}$$

The optimum values of k_j $(j = 1,2,...,20)$ i.e., k_j^* in the equation (3.1), we obtain the minimum MSEs of the considered estimators $\bar{Y}_{PS(j)}$, $(j = 1,2,...,20)$ as

$$MSE_{min}(\bar{Y}_{PS(j)}) = \bar{Y}^2\left[\frac{\left(\frac{1}{n}-\frac{1}{N}\right)\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right)}{1+\left(\frac{1}{n}-\frac{1}{N}\right)\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right)}\right] \tag{3.3}$$

where $(i = 1,2,...,20)$ and $PS_1 = \frac{\bar{X}QD}{\bar{X}QD+D_1}$, $PS_2 = \frac{\bar{X}QD}{\bar{X}QD+D_2}$, $PS_3 = \frac{\bar{X}QD}{\bar{X}QD+D_3}$, $PS_4 = \frac{\bar{X}QD}{\bar{X}QD+D_4}$, $PS_5 = \frac{\bar{X}QD}{\bar{X}QD+D_5}$, $PS_6 = \frac{\bar{X}QD}{\bar{X}QD+D_6}$, $PS_7 = \frac{\bar{X}QD}{\bar{X}QD+D_7}$, $PS_8 = \frac{\bar{X}QD}{\bar{X}QD+D_8}$, $PS_9 = \frac{\bar{X}QD}{\bar{X}QD+D_9}$, $PS_{10} =$

$\frac{\bar{X}QD}{\bar{X}QD+D_{10}}$, $PS_{11}=\frac{\bar{X}D_1}{\bar{X}D_1+QD}$, $PS_{12}=\frac{\bar{X}D_2}{\bar{X}D_2+QD}$, $PS_{13}=\frac{\bar{X}D_3}{\bar{X}D_3+QD}$, $PS_{14}=\frac{\bar{X}D_4}{\bar{X}D_4+QD}$, $PS_{15}=\frac{\bar{X}D_5}{\bar{X}D_5+QD}$, $PS_{16}=\frac{\bar{X}D_6}{\bar{X}D_6+QD}$, $PS_{17}=\frac{\bar{X}D_7}{\bar{X}D_7+QD}$, $PS_{18}=\frac{\bar{X}D_8}{\bar{X}D_8+QD}$, $PS_{19}=\frac{\bar{X}D_9}{\bar{X}D_9+QD}$, $PS_{20}=\frac{\bar{X}D_{10}}{\bar{X}D_{10}+QD}$

4. Efficiency Comparison

The efficiency conditions for the suggested estimators have been derived according to Kadilar and Cingi estimators and Subzar estimators as follows:

4.1. Comparison with Kadilar and Cingi estimators

(1)$MSE(\bar{Y}_{PS(j)}) \leq MSE(\bar{Y}_{KC(i)})$

$$\left[\frac{\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right)}{1+\left(\frac{1}{n}-\frac{1}{N}\right)\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right)}\right] \leq \left(KC_i^2C_x^2+\left(1-\rho^2\right)C_y^2\right) \tag{4.1}$$

where (j = 1, 2, ..., 20; i = 1, 2,....,10)

4.2. Comparison with Subzar estimators

(2)$MSE(\bar{Y}_{PS(j)}) \leq MSE(\bar{Y}_{SU(i)})$,

$$\left(\frac{1}{n}-\frac{1}{N}\right)\left(PS_j^2C_x^2+C_y^2\left(1-\rho^2\right)\right) \geq 0 \tag{4.2}$$

where (j = 1, 2, ..., 20; i = 1,2,....,20) and ($PS_j = SU_i$).
when the conditions (4.1 and 4.2) are justified, the suggested estimators are more dominant estimators than the Subzar et al. [13] and Kadilar and Cingi ([28] & [29]) estimators in this literature.

5. Simulation Study

In this study, a natural population data set has been considered (shown in Table 1) to analyze the behaviour of the suggested estimators over other existing estimators. The suggested estimators $\bar{Y}_{PS(j)}$ $(j = 1, 2, ..., 20)$ are compared with respect to the Subzar et al. [13] and Kadilar and Cingi ([28] & [29]) estimators in this literature. The MSEs of the existing and suggested estimators which are given in Table 2. The RE(%) of the considered estimators $\bar{Y}_{PS(j)}$ (where $j = 1, 2, ..., 20$) with respect to the Subzar et al. [13] and Kadilar and Cingi ([28] & [29]) estimators respectively and computed as the followings:

$$RE(Existing, Suggested) = \frac{MSE(ExistingEstimators)}{MSE_{min}(SuggestedEstimators)} \times 100$$

The values of RE(%) of the considered estimators for various sample sizes which are shown in Tables [3-5].

6. Conclusions

In this work, we have considered some efficient linear regression ratio type estimators and obtained their mean squared errors. From Table 2, it is noticed that the MSEs of the considered estimators are less than other comparable estimators. From Tables [3 - 5], it is also noticed that the relative efficiencies (%) of the suggested estimators involved in simulation studies for various sample sizes. The percent relative efficiencies of the suggested estimators are greater than 100. It is found that our suggested estimators by using the conventional location parameters of an auxiliary variables are more efficient than the Kadilar and Cingi ([28] & [29]) and Subzar et al. [13] estimators. Hence, the behaviours of the suggested estimators are highly justified in simulation studies that may be recommended for further use.

Acknowledgments

The authors would like to express their gratitude to the Editor-in-Chief and the esteemed referees for their informative and constructive suggestions. The authors are also thankful to the National Institute of Technology, Arunachal Pradesh, Jote, for providing the infrastructure required to complete this study.

Table 1: Parameters of natural population data set

(Murthy [30], Page 228)	
$N = 80$	$n = 20$
$\bar{Y} = 5182.637$	$\bar{X} = 1126.463$
$\rho = 0.941$	$S_y = 1835.659$
$C_y = 0.354$	$S_x = 845.610$
$C_x = 0.751$	$\beta_2(x) = -0.063$
$\beta_1(x) = 1.050$	$D_1 = 360$
$D_2 = 460$	$D_3 = 590$
$D_4 = 670$	$D_5 = 750$
$D_6 = 850$	$D_7 = 1480$
$D_8 = 1810$	$D_9 = 2500$
$D_{10} = 3480$	$QD = 588.125$

Table 2: The MSEs of existing and considered estimators for various sample sizes

Existing Estimators	n = 12	n = 16	n = 20	Suggested Estimators	n = 12	n = 16	n = 20
$\bar{Y}_{KC(1)}$	1.10E+06	776719	582539	$\bar{Y}_{PS(1)}$	1.06E+06	754112	569582
$\bar{Y}_{KC(2)}$	1.10E+06	775710	581782	$\bar{Y}_{PS(2)}$	1.06E+06	753897	569418
$\bar{Y}_{KC(3)}$	1.10E+06	776804	582603	$\bar{Y}_{PS(3)}$	1.06E+06	753617	569205
$\bar{Y}_{KC(4)}$	1.12E+06	793008	594756	$\bar{Y}_{PS(4)}$	1.06E+06	753444	569074
$\bar{Y}_{KC(5)}$	1.10E+06	776832	582624	$\bar{Y}_{PS(5)}$	1.05E+06	753272	568943
$\bar{Y}_{KC(6)}$	1.10E+06	775455	581591	$\bar{Y}_{PS(6)}$	1.05E+06	753057	568779
$\bar{Y}_{KC(7)}$	1.10E+06	775037	581277	$\bar{Y}_{PS(7)}$	1.05E+06	751703	567750
$\bar{Y}_{KC(8)}$	1.10E+06	775647	581735	$\bar{Y}_{PS(8)}$	1.05E+06	750995	567211
$\bar{Y}_{KC(9)}$	1.13E+06	797213	597909	$\bar{Y}_{PS(9)}$	1.05E+06	749519	566088
$\bar{Y}_{KC(10)}$	1.10E+06	776809	582607	$\bar{Y}_{PS(10)}$	1.05E+06	747430	564499
$\bar{Y}_{SU(1)}$	1.10E+06	775896	581922	$\bar{Y}_{PS(11)}$	1.05E+06	752818	568598
$\bar{Y}_{SU(2)}$	1.10E+06	775668	581751	$\bar{Y}_{PS(12)}$	1.05E+06	753268	568940
$\bar{Y}_{SU(3)}$	1.10E+06	775372	581529	$\bar{Y}_{PS(13)}$	1.06E+06	753625	569211
$\bar{Y}_{SU(4)}$	1.10E+06	775189	581392	$\bar{Y}_{PS(14)}$	1.06E+06	753776	569326
$\bar{Y}_{SU(5)}$	1.10E+06	775007	581255	$\bar{Y}_{PS(15)}$	1.06E+06	753894	569416
$\bar{Y}_{SU(6)}$	1.10E+06	774779	581084	$\bar{Y}_{PS(16)}$	1.06E+06	754011	569505
$\bar{Y}_{SU(7)}$	1.10E+06	773346	580010	$\bar{Y}_{PS(17)}$	1.06E+06	754385	569789
$\bar{Y}_{SU(8)}$	1.09E+06	772597	579448	$\bar{Y}_{PS(18)}$	1.06E+06	754477	569859
$\bar{Y}_{SU(9)}$	1.09E+06	771035	578276	$\bar{Y}_{PS(19)}$	1.06E+06	754591	569946
$\bar{Y}_{SU(10)}$	1.09E+06	768824	576618	$\bar{Y}_{PS(20)}$	1.06E+06	754675	570010
$\bar{Y}_{SU(11)}$	1.10E+06	774527	580895				
$\bar{Y}_{SU(12)}$	1.10E+06	775002	581252				
$\bar{Y}_{SU(13)}$	1.10E+06	775380	581535				
$\bar{Y}_{SU(14)}$	1.10E+06	775540	581655				
$\bar{Y}_{SU(15)}$	1.10E+06	775665	581749				
$\bar{Y}_{SU(16)}$	1.10E+06	775789	581842				
$\bar{Y}_{SU(17)}$	1.10E+06	776185	582139				
$\bar{Y}_{SU(18)}$	1.10E+06	776282	582212				
$\bar{Y}_{SU(19)}$	1.10E+06	776403	582302				
$\bar{Y}_{SU(20)}$	1.10E+06	776492	582369				

Table 3: RE (%) of the considered estimators $\bar{Y}_{PS(j)}$ $(j = 1, 2, ..., 20)$ over the Kadilar and Cingi estimators $\bar{Y}_{KC(i)}$ $(i = 1, 2, ..., 10)$, respectively.

Estimators	$\bar{Y}_{KC(1)}$	$\bar{Y}_{KC(2)}$	$\bar{Y}_{KC(3)}$	$\bar{Y}_{KC(4)}$	$\bar{Y}_{KC(5)}$	$\bar{Y}_{KC(6)}$	$\bar{Y}_{KC(7)}$	$\bar{Y}_{KC(8)}$	$\bar{Y}_{KC(9)}$	$\bar{Y}_{KC(10)}$
n = 12										
$\bar{Y}_{PS(1)}$	104.203	104.067	104.214	106.388	104.218	104.033	103.977	104.059	106.952	104.215
$\bar{Y}_{PS(2)}$	104.232	104.097	104.243	106.418	104.247	104.063	104.006	104.088	106.982	104.244
$\bar{Y}_{PS(3)}$	104.270	104.135	104.282	106.457	104.286	104.101	104.045	104.126	107.022	104.283
$\bar{Y}_{PS(4)}$	104.294	104.159	104.305	106.481	104.309	104.124	104.068	104.15	107.046	104.306
$\bar{Y}_{PS(5)}$	104.318	104.182	104.329	106.505	104.333	104.148	104.092	104.174	107.070	104.330
$\bar{Y}_{PS(6)}$	104.347	104.211	104.358	106.535	104.362	104.177	104.121	104.203	107.100	104.359
$\bar{Y}_{PS(7)}$	104.533	104.397	104.544	106.725	104.548	104.363	104.306	104.389	107.291	104.545
$\bar{Y}_{PS(8)}$	104.630	104.494	104.642	106.824	104.645	104.460	104.404	104.486	107.391	104.642
$\bar{Y}_{PS(9)}$	104.834	104.698	104.845	107.032	104.849	104.663	104.607	104.689	107.600	104.846
$\bar{Y}_{PS(10)}$	105.124	104.987	105.135	107.328	105.139	104.953	104.896	104.978	107.897	105.136
$\bar{Y}_{PS(11)}$	104.380	104.244	104.391	106.569	104.395	104.210	104.154	104.236	107.134	104.392
$\bar{Y}_{PS(12)}$	104.318	104.183	104.330	106.506	104.333	104.148	104.092	104.174	107.071	104.330
$\bar{Y}_{PS(13)}$	104.269	104.134	104.281	106.456	104.284	104.100	104.043	104.125	107.020	104.281
$\bar{Y}_{PS(14)}$	104.249	104.113	104.260	106.435	104.264	104.079	104.023	104.105	106.999	104.261
$\bar{Y}_{PS(15)}$	104.232	104.097	104.244	106.418	104.248	104.063	104.007	104.089	106.983	104.245
$\bar{Y}_{PS(16)}$	104.216	104.081	104.228	106.402	104.232	104.047	103.991	104.073	106.966	104.229
$\bar{Y}_{PS(17)}$	104.165	104.030	104.177	106.350	104.181	103.996	103.940	104.022	106.914	104.178
$\bar{Y}_{PS(18)}$	104.153	104.018	104.164	106.337	104.168	103.983	103.927	104.009	106.901	104.165
$\bar{Y}_{PS(19)}$	104.137	104.002	104.149	106.321	104.153	103.968	103.912	103.994	106.885	104.149
$\bar{Y}_{PS(20)}$	104.126	103.991	104.137	106.310	104.141	103.956	103.900	103.982	106.873	104.138
n = 20										
$\bar{Y}_{PS(1)}$	102.275	102.142	102.286	104.420	102.290	102.108	102.053	102.134	104.973	102.287
$\bar{Y}_{PS(2)}$	102.304	102.171	102.315	104.450	102.319	102.138	102.083	102.163	105.004	102.316
$\bar{Y}_{PS(3)}$	102.343	102.210	102.354	104.489	102.357	102.176	102.121	102.201	105.043	102.354
$\bar{Y}_{PS(4)}$	102.366	102.233	102.377	104.513	102.381	102.200	102.144	102.225	105.067	102.378
$\bar{Y}_{PS(5)}$	102.390	102.257	102.401	104.537	102.405	102.223	102.168	102.248	105.091	102.402
$\bar{Y}_{PS(6)}$	102.419	102.286	102.430	104.567	102.434	102.253	102.197	102.278	105.122	102.431
$\bar{Y}_{PS(7)}$	102.605	102.472	102.616	104.757	102.620	102.438	102.383	102.463	105.312	102.617
$\bar{Y}_{PS(8)}$	102.702	102.569	102.714	104.856	102.717	102.535	102.480	102.561	105.412	102.714
$\bar{Y}_{PS(9)}$	102.906	102.772	102.917	105.064	102.921	102.739	102.683	102.764	105.621	102.918
$\bar{Y}_{PS(10)}$	103.196	103.062	103.207	105.360	103.211	103.028	102.972	103.053	105.919	103.208
$\bar{Y}_{PS(11)}$	102.452	102.319	102.463	104.600	102.467	102.285	102.230	102.310	105.155	102.464
$\bar{Y}_{PS(12)}$	102.390	102.257	102.401	104.538	102.405	102.224	102.169	102.249	105.092	102.402
$\bar{Y}_{PS(13)}$	102.341	102.209	102.353	104.488	102.356	102.175	102.120	102.200	105.042	102.353
$\bar{Y}_{PS(14)}$	102.321	102.188	102.332	104.467	102.336	102.154	102.099	102.180	105.021	102.333
$\bar{Y}_{PS(15)}$	102.305	102.172	102.316	104.450	102.319	102.138	102.083	102.163	105.004	102.316
$\bar{Y}_{PS(16)}$	102.289	102.156	102.300	104.434	102.304	102.122	102.067	102.147	104.988	102.301
$\bar{Y}_{PS(17)}$	102.238	102.105	102.249	104.382	102.252	102.071	102.016	102.097	104.935	102.249
$\bar{Y}_{PS(18)}$	102.225	102.092	102.236	104.369	102.240	102.059	102.004	102.084	104.922	102.237
$\bar{Y}_{PS(19)}$	102.210	102.077	102.221	104.353	102.224	102.043	101.988	102.068	104.906	102.221
$\bar{Y}_{PS(20)}$	102.198	102.065	102.209	104.341	102.213	102.032	101.977	102.057	104.895	102.210

Table 4: RE (%) of the suggested estimators $\bar{Y}_{PS(j)}$ $(j = 1, 2, ..., 20)$ over the Subzar et al. estimators $\bar{Y}_{SU(i)}$ $(i = 1, 2, ..., 10)$, respectively.

Estimators	$\bar{Y}_{SU(1)}$	$\bar{Y}_{SU(2)}$	$\bar{Y}_{SU(3)}$	$\bar{Y}_{SU(4)}$	$\bar{Y}_{SU(5)}$	$\bar{Y}_{SU(6)}$	$\bar{Y}_{SU(7)}$	$\bar{Y}_{SU(8)}$	$\bar{Y}_{SU(9)}$	$\bar{Y}_{SU(10)}$
n = 12										
$\bar{Y}_{PS(1)}$	104.092	104.062	104.022	103.997	103.973	103.942	103.750	103.650	103.440	103.143
$\bar{Y}_{PS(2)}$	104.122	104.091	104.051	104.027	104.002	103.972	103.779	103.679	103.469	103.173
$\bar{Y}_{PS(3)}$	104.160	104.129	104.090	104.065	104.041	104.010	103.818	103.717	103.507	103.211
$\bar{Y}_{PS(4)}$	104.184	104.153	104.113	104.089	104.064	104.034	103.841	103.741	103.531	103.234
$\bar{Y}_{PS(5)}$	104.207	104.176	104.137	104.112	104.088	104.057	103.865	103.764	103.554	103.257
$\bar{Y}_{PS(6)}$	104.237	104.206	104.166	104.142	104.117	104.086	103.894	103.793	103.583	103.286
$\bar{Y}_{PS(7)}$	104.422	104.391	104.351	104.327	104.302	104.272	104.079	103.978	103.768	103.470
$\bar{Y}_{PS(8)}$	104.519	104.489	104.449	104.424	104.400	104.369	104.176	104.075	103.864	103.567
$\bar{Y}_{PS(9)}$	104.723	104.692	104.652	104.627	104.603	104.572	104.379	104.278	104.067	103.768
$\bar{Y}_{PS(10)}$	105.012	104.981	104.941	104.917	104.892	104.861	104.667	104.566	104.354	104.055
$\bar{Y}_{PS(11)}$	104.269	104.238	104.199	104.174	104.150	104.119	103.926	103.826	103.616	103.319
$\bar{Y}_{PS(12)}$	104.208	104.177	104.137	104.113	104.088	104.058	103.865	103.765	103.555	103.258
$\bar{Y}_{PS(13)}$	104.159	104.128	104.088	104.064	104.039	104.009	103.817	103.716	103.506	103.209
$\bar{Y}_{PS(14)}$	104.138	104.108	104.068	104.043	104.019	103.988	103.796	103.695	103.486	103.189
$\bar{Y}_{PS(15)}$	104.122	104.091	104.052	104.027	104.003	103.972	103.780	103.679	103.470	103.173
$\bar{Y}_{PS(16)}$	104.106	104.076	104.036	104.011	103.987	103.956	103.764	103.663	103.454	103.157
$\bar{Y}_{PS(17)}$	104.055	104.025	103.985	103.960	103.936	103.905	103.713	103.613	103.403	103.107
$\bar{Y}_{PS(18)}$	104.043	104.012	103.972	103.948	103.923	103.893	103.701	103.600	103.391	103.094
$\bar{Y}_{PS(19)}$	104.027	103.997	103.957	103.932	103.908	103.877	103.685	103.585	103.375	103.079
$\bar{Y}_{PS(20)}$	104.016	103.985	103.945	103.921	103.896	103.866	103.674	103.573	103.364	103.068
n = 20										
$\bar{Y}_{PS(1)}$	102.167	102.136	102.097	102.073	102.049	102.019	101.831	101.732	101.526	101.235
$\bar{Y}_{PS(2)}$	102.196	102.166	102.127	102.103	102.079	102.049	101.860	101.761	101.556	101.264
$\bar{Y}_{PS(3)}$	102.234	102.204	102.165	102.141	102.117	102.087	101.898	101.799	101.594	101.302
$\bar{Y}_{PS(4)}$	102.258	102.228	102.189	102.165	102.141	102.110	101.922	101.823	101.617	101.326
$\bar{Y}_{PS(5)}$	102.281	102.251	102.212	102.188	102.164	102.134	101.945	101.846	101.640	101.349
$\bar{Y}_{PS(6)}$	102.311	102.281	102.242	102.217	102.193	102.163	101.974	101.876	101.670	101.378
$\bar{Y}_{PS(7)}$	102.496	102.466	102.427	102.403	102.379	102.349	102.159	102.060	101.854	101.562
$\bar{Y}_{PS(8)}$	102.594	102.563	102.524	102.500	102.476	102.446	102.256	102.157	101.951	101.658
$\bar{Y}_{PS(9)}$	102.797	102.767	102.728	102.703	102.679	102.649	102.459	102.360	102.153	101.860
$\bar{Y}_{PS(10)}$	103.086	103.056	103.017	102.992	102.968	102.938	102.748	102.648	102.441	102.147
$\bar{Y}_{PS(11)}$	102.343	102.313	102.274	102.250	102.226	102.196	102.007	101.908	101.702	101.410
$\bar{Y}_{PS(12)}$	102.282	102.252	102.213	102.189	102.165	102.135	101.946	101.847	101.641	101.350
$\bar{Y}_{PS(13)}$	102.233	102.203	102.164	102.140	102.116	102.086	101.897	101.798	101.593	101.301
$\bar{Y}_{PS(14)}$	102.213	102.182	102.143	102.119	102.095	102.065	101.877	101.778	101.572	101.281
$\bar{Y}_{PS(15)}$	102.196	102.166	102.127	102.103	102.079	102.049	101.860	101.762	101.556	101.265
$\bar{Y}_{PS(16)}$	102.180	102.150	102.111	102.087	102.063	102.033	101.844	101.746	101.540	101.249
$\bar{Y}_{PS(17)}$	102.129	102.099	102.060	102.036	102.012	101.982	101.794	101.695	101.489	101.198
$\bar{Y}_{PS(18)}$	102.117	102.087	102.048	102.024	102.000	101.970	101.781	101.683	101.477	101.186
$\bar{Y}_{PS(19)}$	102.101	102.071	102.032	102.008	101.984	101.954	101.766	101.667	101.462	101.171
$\bar{Y}_{PS(20)}$	102.090	102.060	102.021	101.997	101.973	101.943	101.754	101.656	101.450	101.159

Table 5: RE(%) of the suggested estimators $\bar{Y}_{PS(j)}$ $(j = 1, 2, ..., 20)$ over the Subzar et al. estimators $\bar{Y}_{SU(i)}$ $(i = 11, 12, ..., 20)$, respectively.

Estimators	$\bar{Y}_{SU(11)}$	$\bar{Y}_{SU(12)}$	$\bar{Y}_{SU(13)}$	$\bar{Y}_{SU(14)}$	$\bar{Y}_{SU(15)}$	$\bar{Y}_{SU(16)}$	$\bar{Y}_{SU(17)}$	$\bar{Y}_{SU(18)}$	$\bar{Y}_{SU(19)}$	$\bar{Y}_{SU(20)}$
n = 12										
$\bar{Y}_{PS(1)}$	103.909	103.972	104.023	104.044	104.061	104.078	104.131	104.144	104.160	104.172
$\bar{Y}_{PS(2)}$	103.938	104.002	104.052	104.074	104.091	104.107	104.160	104.174	104.190	104.202
$\bar{Y}_{PS(3)}$	103.976	104.040	104.091	104.112	104.129	104.146	104.199	104.212	104.228	104.240
$\bar{Y}_{PS(4)}$	104.000	104.064	104.114	104.136	104.153	104.169	104.222	104.235	104.252	104.263
$\bar{Y}_{PS(5)}$	104.023	104.087	104.138	104.159	104.176	104.193	104.246	104.259	104.275	104.287
$\bar{Y}_{PS(6)}$	104.053	104.116	104.167	104.189	104.206	104.222	104.275	104.288	104.305	104.317
$\bar{Y}_{PS(7)}$	104.238	104.302	104.353	104.374	104.391	104.408	104.461	104.474	104.490	104.502
$\bar{Y}_{PS(8)}$	104.335	104.399	104.450	104.471	104.488	104.505	104.558	104.571	104.588	104.600
$\bar{Y}_{PS(9)}$	104.538	104.602	104.653	104.675	104.692	104.708	104.762	104.775	104.791	104.803
$\bar{Y}_{PS(10)}$	104.827	104.891	104.942	104.964	104.981	104.998	105.051	105.064	105.081	105.093
$\bar{Y}_{PS(11)}$	104.085	104.149	104.200	104.221	104.238	104.255	104.308	104.321	104.337	104.349
$\bar{Y}_{PS(12)}$	104.024	104.088	104.138	104.160	104.177	104.193	104.246	104.259	104.276	104.288
$\bar{Y}_{PS(13)}$	103.975	104.039	104.090	104.111	104.128	104.145	104.198	104.211	104.227	104.239
$\bar{Y}_{PS(14)}$	103.954	104.018	104.069	104.090	104.107	104.124	104.177	104.190	104.206	104.218
$\bar{Y}_{PS(15)}$	103.938	104.002	104.053	104.074	104.091	104.108	104.161	104.174	104.190	104.202
$\bar{Y}_{PS(16)}$	103.922	103.986	104.037	104.058	104.075	104.092	104.145	104.158	104.174	104.186
$\bar{Y}_{PS(17)}$	103.871	103.935	103.986	104.007	104.024	104.041	104.094	104.107	104.123	104.135
$\bar{Y}_{PS(18)}$	103.859	103.923	103.973	103.995	104.012	104.028	104.081	104.094	104.111	104.122
$\bar{Y}_{PS(19)}$	103.843	103.907	103.958	103.979	103.996	104.013	104.066	104.079	104.095	104.107
$\bar{Y}_{PS(20)}$	103.832	103.896	103.946	103.968	103.985	104.001	104.054	104.067	104.084	104.095
n = 20										
$\bar{Y}_{PS(1)}$	101.986	102.049	102.099	102.12	102.136	102.152	102.204	102.217	102.233	102.245
$\bar{Y}_{PS(2)}$	102.016	102.078	102.128	102.149	102.166	102.182	102.234	102.247	102.263	102.274
$\bar{Y}_{PS(3)}$	102.054	102.116	102.166	102.187	102.204	102.220	102.272	102.285	102.301	102.313
$\bar{Y}_{PS(4)}$	102.077	102.140	102.19	102.211	102.227	102.244	102.296	102.309	102.324	102.336
$\bar{Y}_{PS(5)}$	102.101	102.163	102.213	102.234	102.251	102.267	102.319	102.332	102.348	102.360
$\bar{Y}_{PS(6)}$	102.130	102.193	102.243	102.264	102.280	102.297	102.349	102.362	102.377	102.389
$\bar{Y}_{PS(7)}$	102.315	102.378	102.428	102.449	102.466	102.482	102.534	102.547	102.563	102.575
$\bar{Y}_{PS(8)}$	102.412	102.475	102.525	102.546	102.563	102.579	102.632	102.645	102.661	102.672
$\bar{Y}_{PS(9)}$	102.616	102.679	102.729	102.750	102.766	102.783	102.835	102.848	102.864	102.876
$\bar{Y}_{PS(10)}$	102.904	102.968	103.018	103.039	103.056	103.072	103.125	103.138	103.154	103.166
$\bar{Y}_{PS(11)}$	102.163	102.225	102.275	102.296	102.313	102.329	102.381	102.394	102.410	102.422
$\bar{Y}_{PS(12)}$	102.101	102.164	102.214	102.235	102.251	102.268	102.320	102.333	102.349	102.360
$\bar{Y}_{PS(13)}$	102.053	102.115	102.165	102.186	102.203	102.219	102.271	102.284	102.300	102.312
$\bar{Y}_{PS(14)}$	102.032	102.095	102.144	102.166	102.182	102.198	102.250	102.263	102.279	102.291
$\bar{Y}_{PS(15)}$	102.016	102.079	102.128	102.149	102.166	102.182	102.234	102.247	102.263	102.275
$\bar{Y}_{PS(16)}$	102.000	102.063	102.112	102.133	102.150	102.166	102.218	102.231	102.247	102.259
$\bar{Y}_{PS(17)}$	101.949	102.012	102.061	102.082	102.099	102.115	102.167	102.180	102.196	102.208
$\bar{Y}_{PS(18)}$	101.937	101.999	102.049	102.070	102.086	102.103	102.155	102.168	102.183	102.195
$\bar{Y}_{PS(19)}$	101.921	101.984	102.033	102.054	102.071	102.087	102.139	102.152	102.168	102.180
$\bar{Y}_{PS(20)}$	101.910	101.972	102.022	102.043	102.059	102.076	102.128	102.141	102.156	102.168

References

1. Cochran, W. G., *Sampling Techniques*, 3rd edn, Wiley and Sons, (1977).
2. Sisodia, B. V. S. and Dwivedi, V. K., *A modified ratio estimator using coefficient of variation of auxiliary varianle*, Journal of the Indian Society of Agricultural Statistics, 33 (1), 13-18, (1981).
3. 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).
4. Yan, Z. and Tian, B., *Ratio method to the mean estimation using coefficient of skewness of auxiliary variable*, ICICA 2010. Part 11, CCIS 106,103-110, (2010).
5. Subramani, J. and Kumarapandiyan, G., *Estimation of population Mean using co-efficient of variation and median of an auxiliary variable*, International Journal of Probability and Statistics, (1), 111-118, (2012a).
6. Subramani, J. and Kumarapandiyan, G., *Estimation of population mean using known median and co-efficient of skewness*, American Journal of Mathematics and Statistics, (2), 101-107, (2012b).
7. Subramani, J. and Kumarapandiyan, G., *Modified ratio estimators using known median and co-efficient of kurtosis*, American Journal of Mathematics and Statistics, (2), 95-100, (2012c).
8. Subramani, J. and Kumarapandiyan, G., *A class of modified ratio estimators using Deciles of an auxiliary Variable*, International Journal of Statistical Application, (2), 101-107, (2012d).
9. Swain, A. K. P. C., *An improved ratio type estimator of finite population in sample surveys*, Revista. Invest. Oper., 35 (1), 49-57, (2014).
10. Abid, M., Abbas, N. and Riaz, M., *Enhancing the mean ratio estimators for estimating population mean using non-conventional location parameters*, Revista Colombiana de Estadistica, 39 (1), 63 - 79, (2016a).
11. Abid, M., Abbas, N. and Riaz, M., *Improved modified ratio estimators of population mean based on deciles*, Chiang Mai J. Sci., 43 (1), 1311-1323, (2016b).
12. Abid, M., Abbas, N., Sherwani, K. A. R, and Nazir, Z., H., *Improved ratio estimators for the population mean using non-conventional measures of dispersion*, Pak. Stat. Oper. Res., 12 (2), 353 - 367, (2016c).
13. Subzar, M., Maqbool, S., Raja, T. A., and Shabeer, M., *A new ratio estimators for estimation of population mean using conventional location parameters*, World Applied Sciences Journal, 35 (3), 377-384, (2017).
14. Prasad, S., *Ratio exponential type imputation in sample surveys*, Model Assist Stat Appl, 12 (2), 95 - 106, (2017a).
15. Prasad, S., *An exponential imputation in the case of missing data*,Journal of Statistics and Management Systems, 20 (6), 1127-1140, (2017b).
16. Prasad, S., *Some linear regression type ratio exponential estimators for estimating the population mean based on quartile deviation and deciles*, Statistics in Transition. New Series, 21 (2), 85 - 98, (2020).
17. Koyuncu, N. and Kadilar, C., *Efficient estimators for the population mean*, Hacet J Math Stat , 38 (2), 217 - 225, (2009).
18. Searls, D. T., *The utilization of a known co-efficient of variation in the estimation procedure*, Journal of the American Statistical Association, 59: 308, 1225-1226, (1964).
19. Upadhyaya, L.N., Singh, H.P., Chatterjee, S. and Yadav, R., *A Generalized Family of Transformed Ratio-Product Estimators in Sample Surveys*, Model Assisted Statistics and Applications, 6(2), 137-150, (2011).
20. Subramani, J., & Ajith, S., *Improved ratio cum product estimators for finite population mean with known quartiles and their functions*, SM J. Biometrics Biostat, 2(1), 1008, (2017).
21. Singh, H. P., Pal, S. K., & Solanki, R. S., *A new class of estimators of finite population mean in sample surveys*, Communications in Statistics-Theory and Methods, 46(6), 2630-2637, (2017).
22. Singh, D., Yadav, R. and Chandra, H., *An improved ratio-product-ratio class of estimators for estimating finite population mean*, International Journal of Agricultural and Statistical Sciences, 17 (1), 2021, 119-123, (2021).
23. Yadav, S. K., Dixit, M. K., Dungana, H. N., & Mishra, S. S., *Improved estimators for estimating average yield using auxiliary variable*, International Journal of Mathematical, Engineering and Management Sciences, 4(5), 1228, (2019).
24. Zaman, T., & Kadilar, C., *Novel family of exponential estimators using information of auxiliary attribute*, Journal of Statistics and Management Systems, 22(8), 1499-1509, (2019).
25. Yadav, S. K., & Zaman, T., *Use of some conventional and non-conventional parameters for improving the efficiency of ratio-type estimators*, Journal of Statistics and Management Systems, 24 (5), 1077-1100, (2021).
26. Yadav, V. K., & Prasad, S., *Exponential method of estimation in sampling theory under robust quantile regression methods*, Communications in Statistics-Theory and Methods, 1-19, (2023).
27. Prasad, S., & Yadav, V. K., *Imputation of Missing Data Through Product Type Exponential Methods in Sampling Theory*, Revista Colombiana de Estadística, 46(1), 111-127, (2023).

28. Kadilar, C. and Cingi, H., *Ratio estimators in simple random sampling*, Applied Mathematics and Computaton, 151, 893-902, (2004).

29. 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).

30. Murthy, M. N., *Sampling theory and methods*, Statistical Publishing Society, Calcutta, India, (1967).

Vinay Kumar Yadav,
Assitant Professor,
Department of Data Sciences and Analytics,
School of Social Sciences,
M S Ramaiah University of Applied Sciences
Bengaluru-560054, India.
E-mail address: vkyadavbhu@gmail.com

and

Shakti Prasad (Corresponding author),
Associate Professor,
Department of Mathematics,
National Institute of Technology Jamshedpur,
Jamshedpur-831014, Jharkhand, India
E-mail address: shakti.pd@gmail.com