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Original Article

Comparative Analysis of Ratio-Type Exponential Estimators Using Monte Carlo Simulation

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Abstract *- This paper describes an exponential estimator of ratio-type for the finite population mean that utilizes a single auxiliary variable. Unlike existing estimators, the proposed estimator approach aims to provide a more precise estimate of the population mean. The bias and mean square error of the proposed estimator are derived up to the first order of approximation. A Monte Carlo simulation study has been conducted to evaluate the empirical performance of the proposed estimator. Four types of bivariate population distributions (Normal, Exponential, Uniform, and Gamma)were generated to represent different real-world scenarios with varying degrees of skewness and kurtosis. The Simulation compared the proposed estimator with existing ratio-type and exponential estimators in terms of Mean Squared Error (MSE) and Percent Relative Efficiency (PRE). The simulation results consistently demonstrated that the proposed estimator performs better than the existing estimators. Specifically, it yielded lower MSE values and higher PRE values, indicating greater accuracy and efficiency.*

Keywords *- Ratio Estimator, Bias, Mean Squared Error, Percent Relative Efficiency, Simulation.*

1. Introduction

Sampling becomes inevitable for several reasons, including time and money. To increase efficiency, the estimators using auxiliary information related to the variable of interest have become a powerful technique, particularly in survey sampling. The pioneering work of Cochran (1977) laid the foundation for this approach by introducing the ratio estimator, which utilizes a strongly correlated auxiliary variable to improve estimates of the population mean. This method is particularly effective when there is a strong positive correlation between the auxiliary and study variables. Conversely, when the correlation is negative, product-type estimators have been shown to perform better. Over the years, numerous researchers have built on these foundational concepts by proposing various modifications and enhancements to improve estimator performance. For instance, Bahl and Tuteja (1991)introduced exponential-ratio type estimators that further refined the estimation process by addressing non-linear relationships between variables. Jerajuddin and Kishun (2016), Sisodia and Dwivedi (1981), and Muili and Audu (2019) proposed modified ratio estimators that incorporate parameters such as the sample size and coefficient of variation, thereby increasing flexibility and accuracy. Other notable contributions include those of Singh and Tailor (2003) and Singh et al. (2004), who developed estimators based on supplementary variables and variable transformations under diverse sampling schemes. Estimators utilizing known population parameters, such as the median, were also improved by Subramani and Kumarpandiyan (2013) and Upadhyaya and Singh (1999). Furthermore, Yan and Tian (2010) and Zakari et al. (2020a) incorporated higher-order moments, such as skewness and correlation coefficients, to bring efficacy in estimators in simple random sampling frameworks.

Monte Carlo simulation has become a widely accepted method for validating theoretical results, guiding methodological advancements, and supporting evidence-based recommendations for real-world survey applications in fields like health statistics, agriculture, demography, and market research.
Typically, simulation studies are conducted following these steps:

1. Define a set of assumptions regarding the nature and parameters of the dataset.
2. Create a hypothetical dataset based on these assumptions.
3. Perform statistical analysis on the dataset to estimate the required parameters.
4. To enhance the accuracy of the estimates, repeat steps (2) and (3) multiple times.
5. Analyze the distribution of parameter estimates from the simulated datasets to address the research question of interest.

2. Notations and Symbols

Let $\Psi = \{\Psi_1, \ldots \ldots \ldots, \Psi_N\}$ be a finite population of size N. Let (y_i, x_i) be the i^{th} observation of the study variable Y and auxiliary variable X. Let $\bar{Y}$ and $\bar{X}$ be the population mean of the study variable and auxiliary variable, respectively. Let $s_y^2 = \sum_{i=1}^{n}(y_i - \bar{y})^2/(n-1)$ and $s_x^2 = \sum_{i=1}^{n}(x_i - \bar{x})^2/(n-1)$ be the sample variances and $S_y^2 = \sum_{i=1}^{N}(y_i - \bar{Y})^2/(N-1)$and $S_x^2 = \sum_{i=1}^{n}(x_i - \bar{X})^2/(N-1)$ the population variances of y and x, respectively. Let $C_y = S_y/\bar{Y}$ and $C_x = S_x/\bar{X}$ be the coefficients of variation of y and $x$respectively, and ρ_{yx} The coefficient of correlation between y and x. Consider $\lambda = \left(\frac{1}{n} - \frac{1}{N}\right)$ and $C_{yx} = \rho C_y C_x$.

3. Existing Estimators

Generally, the sample mean $\bar{y}$ is an unbiased estimator of the population mean $\bar{Y}$. The sample mean per unit estimator. $\bar{y}$ and the variance under simple random sampling without replacement is given as

$$T_1 = \bar{y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{1}$$

$$Var(T_1) = \bar{Y}^2 \lambda C_y^2 \tag{2}$$

Cochran suggested the usual ratio estimators for estimating the population mean ($\bar{Y}$) of the study variable (Y) using supplementary information (X). The bias and mean square error are, respectively, given as

$$T_2 = \frac{\bar{y}}{\bar{x}} \bar{X} \tag{3}$$

$$Bias(T_2) = \lambda \bar{Y}\left[C_x^2 - C_{yx}\right] \tag{4}$$

$$MSE(T_2) = \lambda \bar{Y}^2\left[C_y^2 + C_x^2 - 2C_{yx}\right] \tag{5}$$

Sisodia and Dwivedi proposed a ratio-type estimator for the population mean that includes the known coefficient of variation of the auxiliary variable. The expressions for the bias and mean square error of this estimator are as follows:

$$T_3 = \bar{y}\left(\frac{\bar{X} + C_x}{\bar{x} + C_x}\right) \tag{6}$$

$$Bias(T_3) = \lambda \bar{Y}\left[\zeta_1^2 C_x^2 - 2\zeta_1 C_{yx}\right] \tag{7}$$

$$MSE(T_3) = \lambda \bar{Y}^2\left[C_y^2 + \zeta_1^2 C_x^2 - 2\zeta_1 C_{yx}\right] \tag{8}$$

Where, $\zeta_1 = \frac{\bar{X}}{\bar{x} + C_x}$

Upadhyaya and Singh proposed a ratio-type estimator for the finite population mean that incorporates the coefficient of variation and the coefficient of kurtosis.

$$T_4 = \bar{y}\left(\frac{\bar{X} C_x + \beta_2}{\bar{x} C_x + \beta_2}\right) \tag{9}$$

The bias and mean square error of the estimator T_4 are as below

$$Bias(T_4) = \lambda \bar{Y}\left[\zeta_2^2 C_x^2 - 2\zeta_2 C_{yx}\right] \tag{10}$$

$$MSE(T_4) = \lambda \bar{Y}^2\left[C_y^2 + \zeta_2^2 C_x^2 - 2\zeta_2 C_{yx}\right] \tag{11}$$

Where, $\zeta_2 = \frac{\bar{X} C_x}{\bar{x} C_x + \beta_2}$

Singh et al. proposed a new ratio estimator of the population mean by incorporating the coefficient of kurtosis of the auxiliary variable.

$$T_5 = \bar{y}\left(\frac{\bar{X}+\beta_2}{\bar{x}+\beta_2}\right) \tag{12}$$

The bias and mean square error of the estimator T_5 are respectively, given as

$$Bias(T_5) = \lambda\bar{Y}\left[\zeta_3^2 C_x^2 - 2\zeta_3 C_{yx}\right] \tag{13}$$

$$MSE(T_5) = \lambda\bar{Y}^2\left[C_y^2 + \zeta_3^2 C_x^2 - 2\zeta_3 C_{yx}\right] \tag{14}$$

Where, $\zeta_3 = \frac{\bar{X}}{\bar{x}+\beta_2}$

Using the known value of the coefficient of skewness of the auxiliary variable, Yan and Tian proposed a new ratio estimator of the population mean.

$$T_6 = \bar{y}\left(\frac{\bar{X}+\beta_1}{\bar{x}+\beta_1}\right) \tag{15}$$

The bias and mean square error of the estimator T_6 are respectively, given as

$$Bias(T_6) = \lambda\bar{Y}\left[\zeta_4^2 C_x^2 - 2\zeta_4 C_{yx}\right] \tag{16}$$

$$MSE(T_6) = \lambda\bar{Y}^2\left[C_y^2 + \zeta_4^2 C_x^2 - 2\zeta_4 C_{yx}\right] \tag{17}$$

Where, $\zeta_4 = \frac{\bar{X}}{\bar{x}+\beta_1}$

First time Jerajuddin and Kishun used the sample size (n) to enhance the efficiency of the estimator of the population mean. Its bias and mean square error are given as

$$T_7 = \bar{y}\left(\frac{\bar{X}+n}{\bar{x}+n}\right) \tag{18}$$

$$Bias(T_7) = \lambda\bar{Y}\left[\zeta_5^2 C_x^2 - 2\zeta_5 C_{yx}\right] \tag{19}$$

and

$$MSE(T_7) = \lambda\bar{Y}^2\left[C_y^2 + \zeta_5^2 C_x^2 - 2\zeta_5 C_{yx}\right] \tag{20}$$

Where, $\zeta_5 = \frac{\bar{X}}{\bar{x}+n}$

4. Proposed Estimator

The aim of this section is to propose a ratio-type exponential estimator for the population means for the study variable Y using information of the auxiliary variable X with maximum efficiency.

$$T_\Delta = \bar{y}\left(\frac{\bar{X}}{\bar{x}}\right) + \alpha\left\{\bar{X}exp\left(\frac{\bar{X}-\bar{x}}{\bar{X}+\bar{x}}\right) - \bar{x}\right\}, \tag{21}$$

Where α is a suitable constant, whose value is to be determined such that $MSE(T_\Delta)$ is minimum.

Rewriting the above equation in terms ofe's up to the first order of approximation, that is, power up to 2, the equation becomes

$$T_\Delta = \bar{Y}(1+e_y)(1+e_x)^{-1} + \alpha\bar{X}\left(1 - \frac{e_x}{2} + \frac{e_x^2}{4} + \frac{e_x^2}{8}\right) - \alpha\bar{X}(1+e_x)$$

$$T_\Delta - \bar{Y} = -\bar{Y}e_x + \bar{Y}e_x^2 + \bar{Y}e_y - \bar{Y}e_x e_y - \frac{3}{2}\alpha\bar{X}e_x + \frac{3}{8}\alpha\bar{X}e_x^2 \tag{22}$$

To get the expression for bias and mean square error of the proposed ratio-type exponential estimator, the error term $e_y = \frac{\bar{y}-\bar{Y}}{\bar{Y}}$ and $e_x = \frac{\bar{x}-\bar{X}}{\bar{X}}$ have been considered, such that $E(e_y) = E(e_x) = 0$ and $E(e_y^2) = \lambda C_y^2, E(e_x^2) = \lambda C_x^2, E(e_y e_x) = \lambda C_{yx}$

Taking expectation on both sides of equation (22), the bias of the estimator T_Δ is

$Bias(T_\Delta) = \bar{Y}\lambda C_x^2 - \lambda C_{yx} + \frac{3}{8}\alpha\bar{X}\lambda C_x^2$

Squaring and taking expectations on both sides of equation (22), the mean square error of the estimator T_Δ is as given below:

$$MSE(T_\Delta) = \bar{Y}^2\lambda\left(C_y^2 + C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha^2\bar{X}^2\lambda C_x^2 + 3\alpha\bar{X}\bar{Y}\lambda C_x^2 - 3\alpha\bar{Y}\bar{X}\lambda C_{yx} \quad (23)$$

Partially differentiating equation (23) with respect to α and equating it to zero, hence the optimum value of α is

$\alpha_{opt} = \frac{3\bar{Y}\bar{X}\lambda C_{yx} - 3\bar{Y}\bar{X}\lambda C_x^2}{\frac{9}{2}\bar{X}^2\lambda C_x^2}$

$$MSE(T_\Delta)_{min} = \bar{Y}^2\lambda\left(C_y^2 + C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda C_x^2 + 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx} \quad (24)$$

5. Efficiency Comparison

This section provides a mathematical comparison of the mean square error of the proposed estimator and the existing estimators. The proposed estimator is more efficient than the other existing estimators under the following conditions.

i. $-\left[\bar{Y}^2\lambda\left(C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda C_x^2 + 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx}\right] \geq 0$

ii. $-\left[\frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda C_x^2 + 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx}\right] \geq 0$

iii. $\lambda\bar{Y}^2\left[\zeta_1^2 C_x^2 - 2\zeta_1 C_{yx}\right] - \bar{Y}^2\lambda\left(C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda + 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx} \geq 0$

iv. $\lambda\bar{Y}^2\left[\zeta_2^2 C_x^2 - 2\zeta_2 C_{yx}\right] - \bar{Y}^2\lambda\left(C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda + 3\alpha_{opt}\bar{X}\bar{Y}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx} \geq 0$

v. $\lambda\bar{Y}^2\left[\zeta_3^2 C_x^2 - 2\zeta_3 C_{yx}\right] - \bar{Y}^2\lambda\left(C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda + 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx} \geq 0$

vi. $\lambda\bar{Y}^2\left[\zeta_4^2 C_x^2 - 2\zeta_4 C_{yx}\right] - \bar{Y}^2\lambda\left(C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda + 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx} \geq 0$

vii. $\lambda\bar{Y}^2\left[\zeta_5^2 C_x^2 - 2\zeta_5 C_{yx}\right] - \bar{Y}^2\lambda\left(C_x^2 - 2C_{yx}\right) + \frac{9}{4}\alpha_{opt}^2\bar{X}^2\lambda + 3\alpha_{opt}\bar{X}\bar{Y}\lambda C_x^2 - 3\alpha_{opt}\bar{Y}\bar{X}\lambda C_{yx} \geq 0$

Table 1. Generation of a Random Sample from a Specific Distribution Using Python

Distribution	Probability Density Function	Random Variate Code
Normal	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$ $-\infty < x, \mu < \infty$ and $\sigma > 0$	x =np.random.Normal(1.3,1.6,N)
Exponential	$f(x) = \frac{1}{\theta} exp\left[-\frac{\theta}{x}\right]$	x =np.random.Exponential(scale 1/ 0.8, size=N)
Uniform	$f(x) = \begin{cases}\frac{1}{b-a}, a < x < b\end{cases}$	x = np.random.Uniform(-1,3,N)
Gamma	$f(x) = \begin{cases}\frac{a^\lambda e^{-ax} x^{\lambda-1}}{\Gamma(\lambda)}, \ 0 < x < \infty\end{cases}$	x =np.random. Gamma(2,3,N)

It consists of the random seed 1700 for all four distributions.

6. Simulation Study

In this part, a simulation-based method is used to compare the different estimators. This approach involves calculating the mean square error and percent relative efficiency with appropriate parameter values. A simulation study was conducted to compare the efficiency of the proposed estimator and existing estimators. A normal, exponential, uniform, and gamma distribution of X and Y with size N=1700 has been generated using Python programming language. The four different sample sizes are $n = 400,350,300$ and 250 from the simulated population. The conditions under which these populations were generated are given below.

Case-1
(A). Model:$Y = -1 - 2X + \epsilon$, where $X \sim N(1.3,1.6)$

(B). Model:$= 1 + 2X + \epsilon$, where $X \sim N(1.3,1.6)$

The parameters for the normal distribution are $\mu = 1.3$ and $\sigma^2 = 1.6$

Case-2
(A). Model: $Y = -1 - 2X + \epsilon$, where $X \sim exp(0.8)$

(B). Model: $Y = 1 + 2X + \epsilon$, where $X \sim exp(0.8)$

The parameter for the exponential distribution is $\theta = 0.8$

Case-3
(A). Model: $Y = -1 - 2X + \epsilon$, where $X \sim U(-1,3)$

(B). Model: $Y = 1 + 2X + \epsilon$, where $X \sim U(-1,3)$

The parameters for uniform distribution are $a = -1$ and $b = 3$

Case-4
(A). Model: $Y = -1 - 2X + \epsilon$, where $X \sim gamma(2,3)$

(B). Model: $Y = 1 + 2X + \epsilon$, where $X \sim gamma(2,3)$

The parameters for the gamma distribution are $2 = 2$ and $\lambda = 3$

It is assumed that the error term follows a normal distribution with mean ($\mu = 0$) and variance($\sigma^2 = 1$), i.e., $\sim N(0,1)$, for all the model of different cases. Using sample data, Mean Squared Error (MSE) and Percent Relative Efficiency (PRE) for different estimators were computed.

To get a better approximation of results, repeat the above process 100000 times for different distributions with suitable parameters and compute both Mean Squared Error (MSE) and percent relative efficiency of various estimators.

Table 2. Mean Squared Error and Percent Relative Efficiency of Estimators Using Simulation

Case-1						
Population	**Sample**	**Estimators**	**MSE-1(A)**	**PRE-1(A)**	**MSE-1(B)**	**PRE-1(B)**
$N = 1700$	$n = 400$	T_1	0.021411	100	0.021414	100
		T_2	0.004796	446.418398	0.004797	446.363093
		T_3	0.003235	661.797933	0.003254	657.990770
		T_4	0.007045	303.896937	0.007282	294.075443
		T_5	0.008406	254.707404	0.008650	247.554131
		T_6	0.006575	325.619713	0.005383	397.792972
		T_7	0.021230	100.853750	0.021234	100.851604
		T_Δ	**0.001908**	**1121.78148**	**0.001908**	**1121.92166**
Case-2						
Population	**Sample**	**Estimators**	**MSE-2(A)**	**PRE-2(A)**	**MSE-2(B)**	**PRE-2(B)**
		T_1	0.016335	100	0.016333	100
		T_2	0.004544	359.434166	0.004547	359.210148
		T_3	0.003047	536.093572	0.002904	562.422040

$N = 1700$	$n = 350$	T_4	0.011753	138.991263	0.011556	141.345699
		T_5	0.011738	139.162275	0.011541	141.528587
		T_6	0.005317	307.220265	0.005140	317.729540
		T_7	0.016198	100.849103	0.016192	100.874689
		T_Δ	**0.002287**	**714.14507**	**0.002287**	**714.092443**
Case-3						
Population	**Sample**	**Estimators**	**MSE-3(A)**	**PRE-3(A)**	**MSE-3(B)**	**PRE-3(B)**
$N = 1700$	$n = 300$	T_1	0.017307	100	0.017309	100
		T_2	0.006377	271.410483	0.006377	271.400069
		T_3	0.004037	428.698183	0.004092	422.966752
		T_4	0.005207	332.371301	0.005198	332.988123
		T_5	0.005843	296.191151	0.005830	296.883525
		T_6	0.006437	268.841906	0.006458	268.013704
		T_7	0.017162	100.849072	0.017165	100.841422
		T_Δ	**0.002734**	**633.022489**	**0.002732**	**633.552942**
Case-4						
Population	**Sample**	**Estimators**	**MSE-4(A)**	**PRE-4(A)**	**MSE-4(B)**	**PRE-4(B)**
$N = 1700$	$n = 250$	T_1	0.246927	100	0.246968	100
		T_2	0.005129	4814.02771	0.005126	4817.18445
		T_3	0.003685	6699.35358	0.003434	7190.67159
		T_4	0.065521	376.868107	0.068981	358.022512
		T_5	0.044439	555.653109	0.046697	528.871640
		T_6	0.006351	3887.7952	0.005452	4529.54392
		T_7	0.234742	105.191001	0.234403	105.360388
		T_Δ	**0.003433**	**7191.32171**	**0.003433**	**7192.33473**

7. Application

The findings of this study open several avenues for further research and application in the field of survey sampling and statistical estimation. The proposed ratio-type exponential estimator can be extended to more complex sampling designs such as stratified, cluster, or systematic sampling, where auxiliary information is also available and potentially more informative. Future studies can also explore the performance of this estimator in the presence of non-response, measurement errors, or imperfect auxiliary variables, which are common in real-world surveys. Additionally, different population parameters such as total, proportion, or variance can be obtained using this estimator. The application of this study further corroborated the use of real datasets from domains such as public health, agriculture, demography, market research, etc.

8. Conclusion

The aim of this paper is to propose an efficient ratio-type exponential estimator using supplementary information to estimate the finite population means. Therefore, the above studies say that the proposed estimator is more reliable than that of competing estimators. To check the supremacy of the newly proposed estimator against the existing estimators, the bias and mean square error of the proposed ratio-type exponential estimator have been obtained up to the first order of approximation. From the efficiency comparison, it is found that the proposed estimator is more efficient than existing estimators. For the theoretical support, a simulation study has been conducted, and the results of this study are tabulated in Table 2. The results demonstrate that the proposed estimator is more reliable than existing estimators in all situations.

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