

On The Optimum Estimator of Some Modified Ratio and Product Estimators

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Abstract— In the past few decades, estimation of population mean of variable of interest using some known parameters of auxiliary variable with the aim of proposing a more efficient estimators have received wide attention from research community. In this research paper, we obtain the asymptotically optimum estimator of ratio and product estimators of Subramani and Kumarapandiyan using the Optimal C_x Approach proposed in the earlier study. The performance of the optimum estimators was compared with some optimum modified ratio and product estimators in existence using three real-life datasets considered in the literature. The proposed optimum estimators of Subramani and Kumarapandiyan are found to be uniformly better than all optimum estimators that it was compared with.

Keywords-Modified ratio, Modified product, Optimal C_x approach, Asymptotically optimum.

I. INTRODUCTION

Several varieties of classes of Ratio and Product estimators have been established for the past few decades with the aim coming up with a more efficient estimate of the variable of interest by minimizing the bias and MSE using a transformation of the auxiliary variable under different sampling schemes. Among those who worked on these estimators are those proposed by [1], [2], [3], [4], [5], [6] and [7]. This study was motivated by the achievement recorded by [8] on their respective work on “On the Efficiency of Some Modified Ratio and Product Estimators- the Optimal C_x Approach”

This paper aims at improving the estimator proposed by [8] Ratio and Product estimators by using the combination of Median with some other known parameters of the auxiliary variable, such as the Coefficient of Variation, skewness, Kurtosis, Correlation, e.t.c. using simple random sampling scheme.

II. MATERIALS AND METHODS

Consider a finite population $P = (P_1, P_2, P_3, \dots, P_N)$ of N units, a simple random sampling without replacement (SRSWOR). Let y_i and x_i , represent the value of a response variable y and auxiliary variable x , \bar{y} , \bar{x} and \bar{Y} , \bar{X} represent the sample and population mean of the response and auxiliary variable respectively. Furthermore, suppose in a survey dilemma, we are concerned with the estimation of population mean \bar{y} , when the population parameters of the auxiliary variable X are known, such as population mean \bar{X} , coefficient of variation C_x , coefficient of skewness $\beta_1(x)$, coefficient of Kurtosis $\beta_2(x)$ and median M_d based on sample drawn.

Shittu and Adepoju [8] proposed and obtained an optimal estimators of some modified Ratio and Product estimators by minimizing the MSE (.) from each of the estimator with respect to C_x which is obtained by taking the partial derivative of the MSE of the individual estimators with respect to C_x and equate it to zero. Then the C_x optimum is substituted back to the initial MSE to get the modified optimal estimator.

$$\text{i.e } \frac{\partial MSE}{\partial C_x} = 0$$

(1)

The usual estimator

$$T_0 = \bar{y} \tag{2}$$

$$\text{with } Var(T_0) = \frac{1-f}{n} \bar{Y}^2 C_y^2 \tag{3}$$

The Usual Ratio and Product estimators defined by [9] and [10] are respectively given as (4) and (5) respectively

$$T_R = \bar{y} \frac{\bar{X}}{\bar{x}} \tag{4}$$

$$T_p = \bar{y} \frac{\bar{x}}{\bar{X}} \tag{5}$$

Their corresponding MSE are given by (6) and (7) respectively

$$MSE(T_R) = \frac{1-f}{n} \bar{Y}^2 (C_y^2 + C_x^2 - 2\rho C_x C_y) \tag{6}$$

$$MSE(T_P) = \frac{1-f}{n} \bar{Y}^2 (C_y^2 + C_x^2 + 2\rho C_x C_y) \tag{7}$$

The corresponding optimal estimator as defined by [8] are given as (8) and (9) respectively

$$MSE(T_{1(opt)}) = \frac{1-f}{n} \bar{Y}^2 C_y^2 (1 - \rho^2) \tag{8}$$

$$MSE(T_{2(opt)}) = \frac{1-f}{n} \bar{Y}^2 C_y^2 (1 + \rho^2) \tag{9}$$

The ratio and product estimator proposed by [1]

$$T_{R1} = \bar{y} \left(\frac{\bar{X} + C_x}{\bar{x} + C_x} \right) \tag{10}$$

$$T_{P1} = \bar{y} \left(\frac{\bar{x} + C_x}{\bar{X} + C_x} \right) \tag{11}$$

$$MSE(T_{R1}) = \frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_1^2 C_x^2 - 2\lambda_1 \rho C_x C_y) \tag{12}$$

$$MSE(T_{P1}) = \frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_1^2 C_x^2 + 2\lambda_1 \rho C_x C_y) \tag{13}$$

The corresponding optimal estimator define by [8] is given as

$$MSE(T_{R1[opt]}) = \frac{1-f}{n} \bar{Y}^2 C_{y1}^2 (1 - \rho^2) \tag{14}$$

$$MSE(T_{P1[opt]}) = \frac{1-f}{n} \bar{Y}^2 C_{y1}^2 (1 + \rho^2) \tag{15}$$

Where $C_{y1} = \frac{C_x \lambda_1}{\rho}$ and $\lambda_1 = \frac{\bar{X}}{\bar{X} + C_x}$, $\lambda_2 = \frac{\bar{X}}{\bar{X} + \rho}$, $\lambda_3 = \frac{\bar{X}}{\bar{X} + \beta_1}$, $\lambda_4 = \frac{\bar{X}}{\bar{X} + \beta_2}$, $\lambda_5 = \frac{\bar{X} \beta_2}{\bar{X} \beta_2 + C_x}$, $\lambda_6 = \frac{\bar{X}}{\bar{X} + M_d}$, $\lambda_7 = \frac{\bar{X} C_x}{\bar{X} C_x + M_d}$, $\lambda_8 = \frac{\bar{X} \rho}{\bar{X} \rho + M_d}$, $\lambda_9 = \frac{\bar{X} \beta_1}{\bar{X} \beta_1 + M_d}$, $\lambda_{10} = \frac{\bar{X} \beta_2}{\bar{X} \beta_2 + M_d}$.

Table 1: Existing Modified Ratio Estimators with their MSE and Optimum MSE and their Constants.

Estimators	MSE	Optimum MSE	Optimum C_{yi}
$T_{R1} = \bar{y} \left(\frac{\bar{X} + C_x}{\bar{x} + C_x} \right)$ By [1]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_1^2 C_x^2 - 2\lambda_1 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y1}^2 (1 - \rho^2)$	$C_{y1} = \frac{\lambda_1 C_x}{\rho}$
$T_{R2} = \bar{y} \left(\frac{\bar{x} + \rho}{\bar{X} + \rho} \right)$ By [11]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_2^2 C_x^2 - 2\lambda_2 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y2}^2 (1 - \rho^2)$	$C_{y2} = \frac{\lambda_2 C_x}{\rho}$

$T_{R3} = \bar{y} \left(\frac{\bar{X} C_x + \beta_1}{\bar{x} C_x + \beta_1} \right)$ By [12]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_3^2 C_x^2 - 2\lambda_3 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y3}^2 (1 - \rho^2)$	$C_{y3} = \frac{\lambda_3 C_x}{\rho}$
$T_{R4} = \bar{y} \left(\frac{\bar{X} C_x + \beta_2}{\bar{x} C_x + \beta_2} \right)$ By [13]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_4^2 C_x^2 - 2\lambda_4 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y4}^2 (1 - \rho^2)$	$C_{y4} = \frac{\lambda_4 C_x}{\rho}$
$T_{R5} = \bar{y} \left(\frac{\bar{X} \beta_2 + C_x}{\bar{x} \beta_2 + C_x} \right)$ By [13]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_5^2 C_x^2 - 2\lambda_5 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y5}^2 (1 - \rho^2)$	$C_{y5} = \frac{\lambda_5 C_x}{\rho}$
$T_{R6} = \bar{y} \left(\frac{\bar{x} + M_d}{\bar{X} + M_d} \right)$ By [4]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_6^2 C_x^2 - 2\lambda_6 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y6}^2 (1 - \rho^2)$	$C_{y6} = \frac{\lambda_6 C_x}{\rho}$
$T_{R7} = \bar{y} \left(\frac{\bar{X} C_x + M_d}{\bar{x} C_x + M_d} \right)$ By [5]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_7^2 C_x^2 - 2\lambda_7 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y7}^2 (1 - \rho^2)$	$C_{y7} = \frac{\lambda_7 C_x}{\rho}$
$T_{R8} = \bar{y} \left(\frac{\bar{x} \rho + M_d}{\bar{X} \rho + M_d} \right)$ By [6]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_8^2 C_x^2 - 2\lambda_8 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y8}^2 (1 - \rho^2)$	$C_{y8} = \frac{\lambda_8 C_x}{\rho}$
$T_{R9} = \bar{y} \left(\frac{\bar{X} \beta_1 + M_d}{\bar{x} \beta_1 + M_d} \right)$ By [7]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_9^2 C_x^2 - 2\lambda_9 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y9}^2 (1 - \rho^2)$	$C_{y9} = \frac{\lambda_9 C_x}{\rho}$
$T_{R10} = \bar{y} \left(\frac{\bar{X} \beta_2 + M_d}{\bar{x} \beta_2 + M_d} \right)$ By [7]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_{10}^2 C_x^2 - 2\lambda_{10} \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y10}^2 (1 - \rho^2)$	$C_{y10} = \frac{\lambda_{10} C_x}{\rho}$

Table 2: Existing Modified Product Estimators with their MSE and Optimum MSE and their Constants.

Estimators	MSE	Optimum MSE	Optimum C_{yi}
$T_{R1} = \bar{y} \left(\frac{\bar{x} + C_x}{\bar{X} + C_x} \right)$ By [1]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_1^2 C_x^2 + 2\lambda_1 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y1}^2 (1 + \rho^2)$	$C_{y1} = \frac{\lambda_1 C_x}{\rho}$
$T_{R2} = \bar{y} \left(\frac{\bar{x} + \rho}{\bar{X} + \rho} \right)$ By [11]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_2^2 C_x^2 + 2\lambda_2 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y2}^2 (1 + \rho^2)$	$C_{y2} = \frac{\lambda_2 C_x}{\rho}$
$T_{R3} = \bar{y} \left(\frac{\bar{x} C_x + \beta_1}{\bar{X} C_x + \beta_1} \right)$ By [12]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_3^2 C_x^2 + 2\lambda_3 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y3}^2 (1 + \rho^2)$	$C_{y3} = \frac{\lambda_3 C_x}{\rho}$
$T_{R4} = \bar{y} \left(\frac{\bar{x} C_x + \beta_2}{\bar{X} C_x + \beta_2} \right)$ By [13]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_4^2 C_x^2 + 2\lambda_4 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y4}^2 (1 + \rho^2)$	$C_{y4} = \frac{\lambda_4 C_x}{\rho}$
$T_{R5} = \bar{y} \left(\frac{\bar{x} \beta_2 + C_x}{\bar{X} \beta_2 + C_x} \right)$ By [13]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_5^2 C_x^2 + 2\lambda_5 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y5}^2 (1 + \rho^2)$	$C_{y5} = \frac{\lambda_5 C_x}{\rho}$
$T_{R6} = \bar{y} \left(\frac{\bar{x} + M_d}{\bar{X} + M_d} \right)$ By [4]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_6^2 C_x^2 + 2\lambda_6 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y6}^2 (1 + \rho^2)$	$C_{y6} = \frac{\lambda_6 C_x}{\rho}$
$T_{R7} = \bar{y} \left(\frac{\bar{x} C_x + M_d}{\bar{X} C_x + M_d} \right)$ By [5]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_7^2 C_x^2 + 2\lambda_7 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y7}^2 (1 + \rho^2)$	$C_{y7} = \frac{\lambda_7 C_x}{\rho}$

$T_{y8} = \bar{y} \left(\frac{\bar{x}\rho + M_d}{\bar{X}\rho + M_d} \right)$ By [6]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_8^2 C_x^2 + 2\lambda_8 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y8}^2 (1-\rho^2)$	$C_{y8} = \frac{\lambda_8 C_x}{\rho}$
$T_{y9} = \bar{y} \left(\frac{\bar{x}\beta_1 + M_d}{\bar{X}\beta_1 + M_d} \right)$ By [7]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_9^2 C_x^2 + 2\lambda_9 \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y9}^2 (1-\rho^2)$	$C_{y9} = \frac{\lambda_9 C_x}{\rho}$
$T_{y10} = \bar{y} \left(\frac{\bar{x}\beta_2 + M_d}{\bar{X}\beta_2 + M_d} \right)$ By [7]	$\frac{1-f}{n} \bar{Y}^2 (C_y^2 + \lambda_{10}^2 C_x^2 + 2\lambda_{10} \rho C_x C_y)$	$\frac{1-f}{n} \bar{Y}^2 C_{y10}^2 (1-\rho^2)$	$C_{y10} = \frac{\lambda_{10} C_x}{\rho}$

Table 3: Statistics of the Dataset (from [14])

Parameters	Population 1	Population 2	Population 3
N	80	40	80
n	20	20	20
\bar{Y}	51.8264	5141.5363	51.8264
\bar{X}	2.8513	1221.6463	11.2646
ρ	0.9150	0.9244	0.941
C_y	0.3542	0.0557	0.3542
C_x	0.9484	0.0839	0.7507
β_1	0.6978	0.3761	0.5113
β_2	1.3005	-1.5154	2.8664
M_d	1.4800	1184.225	7.575

I. RESULTS

Table 4: The MSE and Optimum MSE of the Existing Modified Ratio Estimators and their Constants. (Population 1 and 2)

Estimators	MSE		Optimum MSE	
	Pop. 1	Pop. 2	Pop. 1	Pop. 2
$T_{R1} = \bar{y} \left(\frac{\bar{X} + C_x}{\bar{x} + C_x} \right)$ By [1]	17.19	992.29	9.91853	791.93
$T_{R2} = \bar{y} \left(\frac{\bar{X} + \rho}{\bar{x} + \rho} \right)$ By [11]	17.68	989.82	10.0964	790.843
$T_{R3} = \bar{y} \left(\frac{\bar{X}C_x + \beta_1}{\bar{x}C_x + \beta_1} \right)$ By [12]	20.66	982.41	11.2979	786.1896
$T_{R4} = \bar{y} \left(\frac{\bar{X}C_x + \beta_2}{\bar{x}C_x + \beta_2} \right)$ By [13]	12.14	995.69	8.0326	815.979

$T_{R5} = \bar{y} \left(\frac{\bar{X}\beta_2 + C_x}{\bar{x}\beta_2 + C_x} \right)$ By [13]	20.7801	995.69	11.1690	792.0398
$T_{R6} = \bar{y} \left(\frac{\bar{X} + M_d}{\bar{x} + M_d} \right)$ By [4]	11.1366	350.49	7.6333	204.2179
$T_{R7} = \bar{y} \left(\frac{\bar{X}C_x + M_d}{\bar{x}C_x + M_d} \right)$ By [5]	10.4605	1625.07 4	7.3575	5.02558
$T_{R8} = \bar{y} \left(\frac{\bar{X}\rho + M_d}{\bar{x}\rho + M_d} \right)$ By [6]	7.2256	370.15	7.17086	188.6968
$T_{R9} = \bar{y} \left(\frac{\bar{X}\beta_1 + M_d}{\bar{x}\beta_1 + M_d} \right)$ By [7]	6.9213	763.35	5.7922	61.8876
$T_{R10} = \bar{y} \left(\frac{\bar{X}\beta_2 + M_d}{\bar{x}\beta_2 + M_d} \right)$ By [7]	14.662	26797.2	8.998	6100.685

Table 5: The MSE and Optimum MSE of the Existing Modified Product Estimators and their Constants. (Population 3)

Estimators	MSE	Optimum MSE
$T_{P1} = \bar{y} \left(\frac{\bar{x} + C_x}{\bar{X} + C_x} \right)$ By [1]	109.78347	6.452479
$T_{P2} = \bar{y} \left(\frac{\bar{x} + \rho}{\bar{X} + \rho} \right)$ By [11]	107.5031	6.2528456
$T_{P3} = \bar{y} \left(\frac{\bar{x}C_x + \beta_1}{\bar{X}C_x + \beta_1} \right)$ By [12]	110.6438	6.527893
$T_{P4} = \bar{y} \left(\frac{\bar{x}C_x + \beta_2}{\bar{X}C_x + \beta_2} \right)$ By [13]	81.94399	4.094738
$T_{P5} = \bar{y} \left(\frac{\bar{x}\beta_2 + C_x}{\bar{X}\beta_2 + C_x} \right)$ By [13]	116.11055	7.01135
$T_{P6} = \bar{y} \left(\frac{\bar{x} + M_d}{\bar{X} + M_d} \right)$ By [4]	63.069711	2.04233
$T_{P7} = \bar{y} \left(\frac{\bar{x}C_x + M_d}{\bar{X}C_x + M_d} \right)$ By [5]	55.020140	2.4970485

$T_{r8} = \bar{y} \left(\frac{\bar{x}\rho + M_d}{\bar{X}\rho + M_d} \right)$ By [6]	61.342855	2.49705
$T_{r9} = \bar{y} \left(\frac{\bar{x}\beta_1 + M_d}{\bar{X}\beta_1 + M_d} \right)$ By [7]	44.99942	2.49705
$T_{r9} = \bar{y} \left(\frac{\bar{x}\beta_2 + M_d}{\bar{X}\beta_2 + M_d} \right)$ By [7]	90.7051866	4.81627

V. DISCUSSION

The main focus of this research paper was to obtain the optimum estimator of Subramani and Kumarapandiyan Ratio and Product estimators which utilize the combination of median with some other known parameters of auxiliary variable in the estimation the population mean of variable of interest based on simple random sampling, which assumed the population to be a homogeneous.

In addition, we support these theoretical results numerically using real-life datasets considered in the literature as shown in Table 3.

Tables 1 & 2 provides the Mean squared error and Optimum mean squared error of some modified ratio and product estimators in existence respectively.

Tables 4 & 5 provides the numerical Mean squared error and Optimum mean squared error of some modified ratio and product estimators in existence respectively.

VI. CONCLUSIONS

Hence we conclude that the estimators in [4], [5], [6] and [7] that utilizes the combination of median and any other known parameter of the auxiliary variable (i.e. mode, coefficient of variation, kurtosis, skewness, e.t.c) have the minimum MSE, and are uniformly more efficient than those that didn't utilizes the median in simple random sampling. Thus, it is preferred to be use in practice.

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