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Variance Estimation Using Linear Combination of Skewness and Quartiles

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Authors' contributions

This work was carried out in collaboration between all authors. Author MAB designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author SM managed the analysis of the study. Authors SAS, AR and SHM managed the literature searches.

All authors read and approved the final manuscript.

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ABSTRACT

In this paper we have suggested Modified ratio type variance estimators where in our aim is to estimate the population variance in the presence of outliers, when there is strong correlation between auxiliary variable and study variable by using, the linear combination of skewness and quartiles as auxiliary information. To judge the efficiency of suggested estimators over existing estimators practically, we have carried out the Bias and Mean square error of proposed and existing estimators and suggested estimators have proven better performance than the existing estimators.

Keywords: Simple random sampling; bias; mean square error; skewness and quartiles efficiency.

1. INTRODUCTION

Here we consider a finite population $U = \{U_1, U_2, ..., U_N\}$ of N distinct and

identifiable units. Let Y be a real variable with value Y_i measured on U_i , i=1,2,3....N given a vector $[Y_1,Y_2,Y_3,.......Y_N]$. Sometimes in sample

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surveys information on auxiliary variable X correlated with study variable Y, is available can be utilized to obtain the efficient estimator for the estimation of Population variance. To estimate the population variance, various efficient estimators have been widely discussed by the authors such as Isaki [1] who proposed ratio and regression estimators. Latter various authors such as Kadilar & Cingi, H [2], have also proposed the ratio estimators to improve the efficiency of modified estimators over existing estimators. Subramani, J. and Kumarapandiyan, G. [3], Kadilar and Cingi, H. [4], have also contributed a lot to the theory of ratio type variance estimation. Similarly, authors such as

Arcos, A., M. Rueda, M. D. Martinez, S. Gonzalez and Y. Roman. [5], who incorporated the auxiliary information available in variance estimation.

Jeelani, Iqbal and Maqbool, S. [6], proposed the modified ratio type estimators for population mean by using linear combination of coefficient of skewness and quartile deviation as auxiliary variables to enhance the efficiency of proposed estimators.

Kadilar, C., and Cingi, H, 2004 [7],suggested new ratio type estimators using correlation coefficient as auxiliary variable. Acordingly, various authors such as, Upadhyaya and Singh [8], Murthy M. N [9] and Singh D, and Chaudhary, F. S. [10] has also modified various estimators to improve the efficiency of existing estimators. "In this paper our aim is to estimate the population variance $S_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on the bases of } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}^N \left(y_i - \overline{y}\right)^2 \text{ on } V_y^2 = \frac{1}{N-1} \sum_{i=1}$

random sample selected from population U" in the presence of outliers.

2. MATERIALS AND METHODS

2.1 Notations

N= Population size. n= Sample size. $\gamma=\frac{1}{n}$ Y= study variable. X= Auxiliary variable. \overline{X} , $\overline{Y}=$, Population means. \overline{x} , $\overline{y}=$ Sample means. S_Y^2 , $S_x^2=$ population variances. S_y^2 , $S_x^2=$ sample variances. C_x , $C_y=$. Coefficient of variation

 $ho = {
m coefficient} \ eta_{{
m l}(x)} = {
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m B} \ (.) = {
m Bias} \ {
m of} \ {
m the} \ {
m estimator}. \ {
m MSE} \ (.) = {
m Mean} \ {
m square} \ {
m error}. \ \hat{S}_R^2 = {
m Ratio} \ {
m type} \ {
m variance} \ {
m estimator}.$

 $\hat{S}_{U\!S1}^2 =$ Existing estimator proposed by Upadhyaya & Singh

 \hat{S}_{Kc1}^2 ,= Existing modified ratio estimator (proposed by Kadilar & Cingi), \hat{S}_{jG}^2 ,= Existing Modified ratio estimator (proposed by J.Subramani & G. Kumarapandian), Q_d = Quartile deviation, Q_a = Quartile average, Q_1 = first quartile, Q_2 = second quartile Q_3 = third quartile $Q_r = Q_3 - Q_1$ quartile range. $\lambda_{rs} = \frac{\mu_{rs}}{\mu_{r0}^{\rho/2} \mu_{r0}^{\rho/2}}$

Where
$$\mu_{rs} = \frac{1}{N} \sum (Y_i - \overline{Y})^r (X_i - \overline{X})^s$$

In this paper, we discuss the already existing estimators in the literature and then proposed modified estimators where we have used the linear combination of skewness and quartiles and accordingly we will compare the results of suggested estimators with the existing estimators.

2.2 Existing Estimators

2.2.1 Ratio type Variance estimator proposed by Upadhyaya and Singh [8]

Isaki suggested a ratio type variance estimator for the population variance $S_{\scriptscriptstyle X}^{\,2}$ when the population variance $S_{\scriptscriptstyle X}^{\,2}$ of the auxiliary variable X is known. Bias and mean square error is given by

$$\hat{S}_{US1}^2 = s_y^2 \left[\frac{S_x^2 + \beta_{2x}}{s_x^2 + \beta_{2x}} \right] \tag{1}$$

Bias
$$((\hat{S}_R^2) = \gamma S_y^2 [(\beta_{2(x)} - 1) - (\lambda_{22} - 1)]$$
 (2)

MSE
$$((\hat{S}_R^2) = \gamma S_y^4 [(\beta_{2(y)} - 1) + (\beta_{2(x)} - 1) - 2(\lambda_{22} - 1)]$$
 (3)

2.2.2 Ratio type variance estimator proposed by Kadilar and Cingi [2]

The authors have suggested ratio type variance estimators where they have used known values of Coefficient of variance and coefficient of kurtosis as an auxiliary variable X, whose Bias, mean square and percent relative efficiency has been shown in Table-1, Table-2, Table-3, Table-4 and Table-5

$$\hat{S}_{kc1}^2 = S_y^2 \left[\frac{S_x^2 + C_x}{S_x^2 + C_x} \right] \tag{4}$$

Bias (
$$(\hat{S}_{kc1}^2) = \gamma S_y^2 A_1 \left[A_1 \left(\beta_{2(x)} - 1 \right) - (\lambda_{22} - 1) \right]$$
 (5)

MSE
$$((\hat{S}_{kc1}^2) = \gamma S_y^4 [(\beta_{2(y)} - 1) + A_1^2 (\beta_{2(x)} - 1) - 2A_1 (\lambda_{22} - 1)]$$
 (6)

2.2.3 Ratio type variance estimator proposed by J. Subramani & G. Kumara pandiyan [3]

The authors have suggested ratio type variance estimators and they have used median, quartiles and Deciles as an auxiliary variable X, whose bias, mean square error and percent relative efficiency is given in Table-1, Table-2, Table-3, Table-4 and Table-5 respectively

$$\hat{S}_{jG}^{2} = S_{y}^{2} \left[\frac{S_{x}^{2} + \alpha w_{i}}{S_{x}^{2} + \alpha w_{i}} \right]$$
 (7)

Bias
$$((\hat{S}_{jG}^2) = \gamma S_y^2 A_{jG} [A_{jG}(\beta_{2(x)} - 1) - (\lambda_{22} - 1)]$$

Mse (\hat{S}_{jG}^2)
 $\gamma S_y^4 [(\beta_{2(y)} - 1) + A_{jG}^2 (\beta_{2(x)} - 1) - 2A_{jG}(\lambda_{22} - 1)]$
(8)

2.3 Proposed Estimator

We modified have proposed new ratio type variance estimator of the auxiliary variable by using linear combination skewness and quartiles. quartiles are not sensitive to outliers, as they divide the series into different series and provide various location parameters and shape shifts, accounts the distributional properties and also estimates the covariate effects of average value

$$\begin{split} \hat{S}_{MS1}^2 &= s_y^2 \Bigg[\frac{S_x^2 + (\beta_1 + Q_1)}{s_x^2 + (\beta_1 + Q_1)} \Bigg] \ \hat{S}_{MS2}^2 = s_y^2 \Bigg[\frac{S_x^2 + (\beta_1 + Q_2)}{s_x^2 + (\beta_1 + Q_2)} \Bigg] \\ \hat{S}_{MS3}^2 &= s_y^2 \Bigg[\frac{S_x^2 + (\beta_1 + Q_3)}{s_x^2 + (\beta_1 + Q_3)} \Bigg] \hat{S}_{MS4}^2 = s_y^2 \Bigg[\frac{S_x^2 + (\beta_1 + Q_d)}{s_x^2 + (\beta_1 + Q_d)} \Bigg] \\ \hat{S}_{MS5}^2 &= s_y^2 \Bigg[\frac{S_x^2 + (\beta_1 + Q_a)}{s_x^2 + (\beta_1 + Q_a)} \Bigg] \ \hat{S}_{MS6}^2 = s_y^2 \Bigg[\frac{S_x^2 + (\beta_1 + Q_r)}{s_x^2 + (\beta_1 + Q_r)} \Bigg] \end{split}$$

Here we have derived the bias and mean square error of the proposed estimator \hat{S}^2_{MSi} ; i=1,2,....,6 up to the first order of approximation as given below:

Let
$$e_0=\frac{s_y^2-S_y^2}{S_y^2}$$
 and $e_1=\frac{s_x^2-S_x^2}{S_x^2}$. Further we can write $s_y^2=S_y^2(1+e_0)$ and $s_x^2=S_x^2(1+e_0)$ and from the definition of e_0 and e_1 we obtain:

$$E[e_0] = E[e_1] = 0, \quad E[e_0^2] = \frac{1 - f}{n} (\beta_{2(y)} - 1),$$

$$E[e_1^2] = \frac{1 - f}{n} (\beta_{2(x)} - 1), \quad E[e_0 e_1] = \frac{1 - f}{n} (\lambda_{22} - 1)$$

The proposed estimator $\hat{S}_{\mathit{MSi}}^{\,2}\,;\;i=1,2,...,6$ is given below:

$$\hat{S}_{MSi}^{2} = s_{y}^{2} \left[\frac{S_{x}^{2} + \alpha a_{i}}{s_{x}^{2} + \alpha a_{i}} \right]$$

$$\Rightarrow \quad \hat{S}_{MSi}^{2} = s_{y}^{2} (1 + e_{0}) \left[\frac{S_{x}^{2} + \alpha a_{i}}{s_{x}^{2} + e_{1} S_{x}^{2} + \alpha a_{i}} \right]$$

$$\Rightarrow \quad \hat{S}_{MSi}^{2} = \frac{S_{y}^{2} (1 + e_{0})}{(1 + A_{MSi} e_{1})}$$
Where $A_{MSi} = \frac{S_{x}^{2}}{S_{x}^{2} + \alpha a_{i}}$

is a constant and MS_i, i=1,2.....6 suggested estimators and $a_i = (\beta_1 + Q_i)$; i = 1,2,3,d,a,r

$$\Rightarrow \hat{S}_{MSi}^2 = S_v^2 (1 + e_0) (1 + A_{MSi} e_1)^{-1}$$
 (2)

$$\Rightarrow \begin{array}{l} \hat{S}_{MSi}^{2} = S_{y}^{2} (1 + e_{0}) (1 - A_{MSi} e_{1} + A_{MSi}^{2} e_{1}^{2} \\ - A_{MSi}^{3} e_{1}^{3} +) \end{array}$$
 (3)

Table 1. Bias and MSE of existing estimators

Population 1			Po	pulation 2	Population 3	
Existing estimator	Bias	Mean square error	Bias	Mean square error	Bias	Mean square error
Upadhyaya & Singh [8]	6.88	2678.64	189.61	8285277.52	267.48	8662043.54
Kadilar&Cingi [2]	7.51	2806.20	193.45	8305040.92	274.87	8700066.36
Subramani &	6.22	2551.09	194.29	8309384.71	276.27	8707285.44
Kumarapandiyan [3]						

Expanding and neglecting the terms more than 3^{rd} order, we get

$$\hat{S}_{MSi}^2 = S_v^2 + S_v^2 e_0 - S_v^2 A_{MSi} e_1 - S_v^2 A_{MSi} e_0 e_1 + S_v^2 A_{MSi}^2 e_1^2$$
 (4)

$$\Rightarrow \hat{S}_{MSi}^2 - S_v^2 = S_v^2 e_0 - S_v^2 A_{MSi} e_1 - S_v^2 A_{MSi} e_0 e_1 + S_v^2 A_{MSi}^2 e_1^2$$
 (5)

By taking expectation on both sides of (5), we get

$$\begin{split} E(\hat{S}_{MSi}^{2} - S_{y}^{2}) &= S_{y}^{2} E(e_{0}) - S_{y}^{2} A_{MSi} E(e_{1}) \\ - S_{y}^{2} A_{MSi} E(e_{0}e_{1}) + S_{y}^{2} A_{MSi}^{2} E(e_{1}^{2}) \\ Bias(\hat{S}_{MSi}^{2}) &= S_{y}^{2} A_{MSi}^{2} E(e_{1}^{2}) - S_{y}^{2} A_{MSi} E(e_{0}e_{1}) \\ Bias(\hat{S}_{MSi}^{2}) &= \gamma S_{y}^{2} A_{MSi} [A_{MSi}(\beta_{2(x)} - 1) - (\lambda_{22} - 1)] \end{split} \tag{6}$$

Squaring both sides of (5) and (6), neglecting the terms more than 2nd order and taking expectation, we get

$$E(\hat{S}_{MSi}^{2} - S_{y}^{2})^{2} = S_{y}^{4} E(e_{0}^{2})$$

$$+ S_{y}^{4} A_{MSi}^{2} E(e_{1}^{2}) - 2 S_{y}^{4} A_{MSi} E(e_{0} e_{1})$$

$$MSE(\hat{S}_{MSi}^{2}) = \gamma S_{y}^{4} [(\beta_{2(y)} - 1) + A_{MSi}^{2} (\beta_{2(y)} - 1) - 2 A_{MSi} (\lambda_{22} - 1)]$$

3. RESULTS AND DATA ANALYSIS

3.1 Numerical Illustration

3.1.1 Population-1

We use the data of Murthy [9] page 228 in which fixed capital is denoted by X(auxiliary variable) and output of 80 factories are denoted by

Population-3 Singh & Chaudhary [10]

$$N = 80$$
, $n = 20$, $S_x = 8.4563$, $C_x = 0.7507$, $S_y = 18.3569$, $\overline{Y} = 51.8264$, $\beta_{1x} = 1.05$, $\beta_{2x} = 2.8664$, $\beta_{2y} = 2.2667$, $\lambda_{22} = 2.2209$, $Q_1 = 9.31$, $Q_2 = 7.5750$, $Q_3 = 16.9750$, $Q_r = 11.82$, $Q_a = 11.0625$, $Q_d = 5.9125$, $\overline{X} = 11.2624$

3.1.2 Population-2

We have taken population-2 from Singh & Chaudhary (1986) given in page 177

Population-2: Singh and Chaudhary [10]

$$\begin{split} N &= 34 \ , \ n = 20 \ , \ \overline{Y} = 85.64 \ , \ \overline{X} = 20,\!88 \ , \\ S_y &= 73.31 \\ S_x &= 15.05, \beta_{1x} = 0.8732, \beta_{2x} = 2.91, \beta_{2y} = 13.36, \\ \lambda_{22} &= 1.1525, Q_1 = 9.42, Q_2 = 15.0, Q_3 = 25.47, \\ Q_x &= 16.05, Q_a = 17.45, Q_d = 16.05, C_x = 0.7205 \end{split}$$

3.1.3 Population-3

We have taken population-3 again from Singh & Chaudhary (1986) given in page 177.

 $N = 34, n = 20, \overline{Y} = 85.64, \overline{X} = 19.94, S_y = 73.31, \lambda_{22} = 1.2244.S_x = 15.02, C_x = 0.7532.\beta_{2x} = 3.7257, \beta_{2y} = 13.3666, \beta_{1x} = 1.2758, Q_1 = 9.925, Q_2 = 14.25, Q_3 = 27.8, Q_r = 17.87.Q_a = 18.86.Q_d = 8.9375$

Table 2. Bias and MSE of proposed estimators

Population-1			Po	pulation-2	Population-3		
Existing estimator	Bias	Mean square	Bias	Mean Bias		Mean	
		error		square error		square error	
Upadhyaya & Singh [8]	6.88	2678.64	189.61	8285277.52	267.48	8662043.54	
Kadilar & Cingi [2]	7.51	2806.20	193.45	8305040.92	274.87	8700066.36	
Subramani &	6.22	2551.09	194.29	8309384.71	276.27	8707285.44	
Kumarapandiyan [3]							
MS ₁	5.91	2508.57	176.24	817622.78	248.59	852774.58	
MS_2	5.32	2381.01	168.05	813275.44	238.83	847345.97	
MS_3	3.20	2125.91	153.51	805873.95	213.32	834887.79	
MS ₄	4.31	2253.46	165.96	812979.38	231.92	844302.48	
MS ₅	4.46	2254.46	164.49	811795.14	229.82	843064.95	
MS ₆	5.75	2466.05	165.96	812929.38	250.23	853302.69	

Table 3. Percent relative efficiency of proposed estimators with existing estimators for Population-1

Estimators	P1	P2	P3	P4	P5	P6
Upadhyaya & Singh [8]	106.77	112.50	125.99	118.86	118.86	108.62
Kadilar & Cingi [2]	111.86	117.85	131.99	124.52	124.52	113.79
Subramani & Kumarapandiyan [3]	101.69	107.14	119.99	113.20	113.20	103.44

Table 4. Percent relative efficiency of proposed estimators with existing estimators for Population-2

Estimators	P1	P2	P3	P4	P5	P6
Upadhyaya & Singh [8]	1013.33	1018.75	1028.11	1019.12	1020.61	1019.18
Kadilar & Cingi [2]	1015.75	1021.18	1030.56	1021.55	1023.04	1021.61
Subramani & Kumarapandiyan [3]	1016.28	1021.71	1031.10	1022.09	1023.58	1022.15

Table 5. Percent relative efficiency of proposed estimators with existing estimators for Population-3

Estimators	P1	P2	P3	P4	P5	P6
Upadhyaya & Singh [8]	1015.74	1022.25	1037.51	1025.94	1027.44	1015.69
Kadilar & Cingi [2]	1020.20	1026.74	1042.06	1030.44	1031.95	1019.57
Subramani & Kumarapandiyan [3]	1021.05	1027.59	1042.92	1031.29	1032.81	1020.42

4. CONCLUSION AND LIMITATION

In this paper, the above tables have clearly revealed that our proposed estimators are more efficient than the existing estimators when the comparison is made between the existing and proposed estimators together with their percent relative efficiency criteria. Hence the proposed estimator may be preferred over existing estimators for use in practical applications. Furthermore, the advantage of using these methods to estimate the population variance is that they are not sensitive to outliers, but with an disadvantage that they can be further modified to improve the efficiency of the variance estimators.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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