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MEDIAN BASED MODIFIED RATIO ESTIMATORS WITH KNOWN SKEWNESS AND CORRELATION COEFFICIENT FOR THE ESTIMATION OF FINITE POPULATION MEAN

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Abstract

In this study, two new median based modified ratio estimators with the linear combinations of population correlation coefficient and skewness of an auxiliary variable have been proposed. The bias and mean squared error of the proposed estimators are obtained and the efficiencies of the proposed estimators are compared with that of the simple random sampling without replacement (SRSWOR) sample mean, the usual ratio estimator, the corresponding modified ratio estimators, the linear regression estimator and the median based ratio estimator for certain natural populations. It is shown from the numerical study that the proposed median based modified ratio estimators are outperformed all the existing estimators mentioned above including the linear regression estimator.

Key Words: Bias, Linear Regression Estimator, Mean Squared Error, Natural Population, Simple Random Sampling.

1. Introduction

Consider a finite population $U = \{U_1, U_2, \ldots, U_N\}$ of N distinct and identifiable units. Let Y be the study variable with value Y_i measured on $U_i, i = 1, 2, 3, \ldots, N$ giving a vector $Y = \{Y_1, Y_2, \ldots, Y_N\}$. The problem is to estimate the population mean $\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i$ with some desirable properties like unbiased, minimum variance etc., on the basis of a random sample selected from the population $U = \{U_1, U_2, \ldots, U_N\}$. The simplest estimator of a finite population mean is the sample mean obtained from the simple random sampling without replacement, when there is no auxiliary information available. Suppose there is an auxiliary variable X which is positively correlated with the study variable Y, then ratio estimator and linear regression estimator can be used to improve the efficiency of the estimator based on SRSWOR under certain conditions. To know more about the ratio and regression estimators and other related results one may refer Cochran (1977) and Murthy (1967). When the population parameters of the auxiliary variable X such as population mean, coefficient of variation, kurtosis, skewness and median are known, a number of modified ratio estimators are proposed in the literature, by extending the usual ratio and linear regression estimators.

In the case of simple random sampling without replacement (SRSWOR), the sample mean $\bar{y}$ is used to estimate the population mean $\bar{Y}$. The SRSWOR estimator of $\bar{Y}$ is $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ and its variance is

$$V(\bar{y}) = \frac{1-f}{n} S_y^2 \tag{1.1}$$

where $f = \frac{n}{N}$; $S_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(Y_i - \bar{Y})^2$

The classical Ratio estimator for estimating the population mean $\bar{Y}$ of the study variable Y is defined as $\hat{\bar{Y}}_R = \frac{\bar{y}}{\bar{x}}\bar{X} = \hat{R}\bar{X}$. The bias and mean squared error of $\hat{\bar{Y}}_R$ are as given below:

$$B\left(\hat{\bar{Y}}_R\right) = \bar{Y}\left\{C'_{xx} - C'_{yx}\right\} \tag{1.2}$$

$$MSE\left(\hat{\bar{Y}}_R\right) = V(\bar{y}) + R^2 V(\bar{x}) - 2RCov(\bar{y}, \bar{x}) \tag{1.3}$$

where $R = \frac{\bar{Y}}{\bar{X}}$, $C'_{xx} = \frac{V(\bar{x})}{\bar{X}^2}$, $C'_{yx} = \frac{Cov(\bar{y},\bar{x})}{\bar{X}\bar{Y}}$, $V(\bar{x}) = \frac{1}{^{N}C_n}\sum_{i=1}^{^{N}C_n}(\bar{x}_i - \bar{X})^2 = \frac{1-f}{n} S_x^2$,

$Cov(\bar{y}, \bar{x}) = \frac{1}{^{N}C_n}\sum_{i=1}^{^{N}C_n}(\bar{x}_i - \bar{X})(\bar{y}_i - \bar{Y}) = \frac{1-f}{n}\frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})$

The other important estimator using the auxiliary variable X is the linear regression estimator. The linear regression estimator and its optimum variance are given below:

$$\hat{\bar{Y}}_{lr} = \bar{y} + \beta(\bar{X} - \bar{x}) \tag{1.4}$$

$$V\left(\hat{\bar{Y}}_{lr}\right) = V(\bar{y})(1 - \rho^2) \tag{1.5}$$

where ρ is the population correlation co-efficient between X and Y

Subramani (2013) has proposed modified ratio estimators for estimating $\bar{Y}$ using the linear combination of population correlation coefficient and coefficient of skewness of auxiliary variable and are given by,

$$\hat{\bar{Y}}_{RM1} = \bar{y}\left(\frac{\rho\bar{X} + \beta_1}{\rho\bar{x} + \beta_1}\right) \tag{1.6}$$

$$\hat{\bar{Y}}_{RM2} = \bar{y}\left(\frac{\beta_1\bar{X} + \rho}{\beta_1\bar{x} + \rho}\right) \tag{1.7}$$

where $\beta_1 = \frac{{\mu_3}^2}{\mu_2^3}$ where $\mu_r = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{X})^r$ is coefficient of skewness of the auxiliary variable

The bias and the mean squared error of the above modified ratio estimators given in (1.6) and (1.7) are combined into a class of estimators since the expressions differ only by the known constant and are given below:

$$B\left(\hat{\bar{Y}}_{RMi}\right) = \bar{Y}\{\theta_i^2 C'_{xx} - \theta_i C'_{yx}\} \tag{1.8}$$

$$MSE\left(\hat{\bar{Y}}_{RMi}\right) = V(\bar{y}) + R^2\theta_i^2 V(\bar{x}) - 2R\theta_i Cov(\bar{y},\bar{x}) \tag{1.9}$$

where $\theta_1 = \frac{\rho\bar{X}}{\rho\bar{X}+\beta_1}$; $\theta_2 = \frac{\beta_1\bar{X}}{\beta_1\bar{X}+\rho}$; $i = 1,2$

Subramani and Prabavathy (2014) have suggested a new ratio estimator namely median based ratio estimator for estimating $\bar{Y}$ when the median of the study variable Y is known. The median based ratio estimator $\hat{\bar{Y}}_M = \bar{y}\frac{M}{m}$ and its bias and mean squared error are as follows:

$$B\left(\hat{\bar{Y}}_M\right) = \bar{Y}\left\{C'_{mm} - C'_{ym} - \frac{Bias(m)}{M}\right\} \tag{1.10}$$

$$MSE\left(\hat{\bar{Y}}_M\right) = V(\bar{y}) + R'^2 V(m) - 2R' Cov(\bar{y}, m) \tag{1.11}$$

where $R' = \frac{\bar{Y}}{M}$, $Bias\ (m) = \bar{M} - M$, $MSE(m) = V(m) = \frac{1}{N_{C_n}}\sum_{i=1}^{N_{C_n}}(m_i - M)^2$, $Cov(\bar{y}, m) = \frac{1}{N_{C_n}}\sum_{i=1}^{N_{C_n}}(m_i - M)(\bar{y}_i - \bar{Y})$, $C'_{mm} = \frac{V(m)}{M^2}$, $C'_{ym} = \frac{Cov(\bar{y},m)}{M\bar{Y}}$, m is the sample median, M is the population median and $\bar{M} = \frac{1}{N_{C_n}}\sum_{i=1}^{N_{C_n}} m_i$

In fact the estimator $\hat{\bar{Y}}_M$ has performed better than the estimators based on SRSWOR, ratio method of estimation and linear regression method of estimation.

Several other estimators are proposed in literature to achieve further improvements by extending the usual ratio and linear regression estimators with known population parameters of the auxiliary variable such as coefficient of variation, skewness, kurtosis, correlation coefficient, quartiles and their linear combinations. See for example, Kadilar and Cingi (2004, 2006a, b, 2009), Koyuncu and Kadilar (2009), Singh and Kakran (1993), Singh and Tailor (2003, 2005), Singh (2003), Sisodia and Dwivedi (1981), Subramani and Kumarapandiyan (2012a, b, c, 2013), Subramani (2013), Tailor and Sharma (2009), Tin (1965), Yan and Tian (2010) and the references cited therein.

By extending the work of Subramani and Prabavathy (2014), two new median based modified ratio estimators with the linear combinations of known correlation coefficient and skewness of the auxiliary variable have been proposed. The proposed estimators along with their biases and the mean squared errors are given in Section 2.

2. Proposed median based modified ratio estimators

The proposed median based modified ratio estimators for the estimation of population mean $\bar{Y}$ using the linear combination of correlation coefficient and skewness of an auxiliary variable are given by,

$$\hat{\bar{Y}}_{SP1} = \bar{y}\left(\frac{\rho M+\beta_1}{\rho m+\beta_1}\right) \quad (2.1)$$

$$\hat{\bar{Y}}_{SP2} = \bar{y}\left(\frac{\beta_1 M+\rho}{\beta_1 m+\rho}\right) \quad (2.2)$$

By neglecting the term of higher orders, the bias and mean squared error of $\hat{\bar{Y}}_{SPj}$ are obtained as given below.

$$B\left(\hat{\bar{Y}}_{SPj}\right) = \bar{Y}\left\{\theta_j'^2\, C'_{mm} - \theta_j' C'_{ym} - \theta_j' \frac{Bias(m)}{M}\right\} \quad (2.3)$$

$$MSE\left(\hat{\bar{Y}}_{SPj}\right) = V(\bar{y}) + R'^2\theta_j'^2 V(m) - 2R'\theta_j' Cov(\bar{y}, m) \quad (2.4)$$

where $\theta_1' = \frac{\rho M}{\rho M+\beta_1}$, $\theta_2' = \frac{\beta_1 M}{\beta_1 M+\rho}$, $j = 1, 2$

3. Efficiency comparison

In this section the algebraic efficiency of the proposed median based modified ratio estimators with respect to SRSWOR sample mean, ratio estimator, modified ratio estimators, linear regression estimator and median based ratio estimator are discussed.

3.1. Comparison with that of SRSWOR sample mean

Comparing (2.4) and (1.1), we arrive at the proposed estimator $\hat{\bar{Y}}_{SPj}$, $j = 1, 2$ is more efficient than the SRSWOR sample mean $\bar{y}$ That is,

$$MSE(\hat{\bar{Y}}_{SPj}) \leq V(\bar{y}) \text{ , if } 2C'_{ym} \geq \theta_j'\, C'_{mm} \;;\; j = 1, 2 \quad (3.1)$$

3.2. Comparison with that of ratio estimator

Comparing (2.4) and (1.3), we arrive at the proposed estimator $\hat{\bar{Y}}_{SPj}$, $j = 1, 2$ is more efficient than the usual ratio estimator $\hat{\bar{Y}}_R$. That is,

$$MSE\left(\hat{\bar{Y}}_{SPj}\right) \leq V\left(\hat{\bar{Y}}_R\right), \text{ if } \theta_j'^2\, C'_{mm} - C'_{xx} \leq 2\left\{\theta_j'\, C'_{ym} - C'_{yx}\right\} \;;\; j = 1, 2 \quad (3.2)$$

3.3. Comparison with that of modified ratio estimators

Comparing (2.4) and (1.9), we arrive at the proposed estimator $\hat{\bar{Y}}_{SPj}$, $j = 1,2$ is more efficient than the existing modified ratio estimator $\hat{\bar{Y}}_{RMi}$, $i = 1,2$. That is,

$$MSE\left(\hat{\bar{Y}}_{SPj}\right) \leq MSE\left(\hat{\bar{Y}}_{RMi}\right), \text{ if } {\theta'_j}^2 C'_{mm} - \theta_i^2 C'_{xx} \leq 2\left(\theta'_j C'_{ym} - \theta_i C'_{yx}\right), \; i, j = 1,2 \tag{3.3}$$

3.4. Comparison with that of linear regression estimator

Comparing (2.4) and (1.5), we arrive at the proposed estimator $\hat{\bar{Y}}_{SPj}$, $j = 1,2$ is more efficient than the usual linear regression estimator $\hat{\bar{Y}}_{lr}$. That is,

$$MSE\left(\hat{\bar{Y}}_{SPj}\right) \leq V\left(\hat{\bar{Y}}_{lr}\right), \text{ if } 2\theta'_j C'_{ym} - {\theta'_j}^2 C'_{mm} \geq \frac{[C'_{yx}]^2}{C'_{xx}}; j = 1,2 \tag{3.4}$$

3.5 Comparison with that of median based ratio estimator

Comparing (2.4) and (1.11) we arrive at the proposed estimator $\hat{\bar{Y}}_{SPj}$, $j = 1,2$ is more efficient than the median based ratio estimator $\hat{\bar{Y}}_{M}$. That is,

$$MSE\left(\hat{\bar{Y}}_{SPj}\right) \leq MSE\left(\hat{\bar{Y}}_{M}\right), \text{ if } 2C'_{ym} \leq \left(\theta'_j + 1\right)C'_{mm} ; \; j = 1,2 \tag{3.5}$$

4. Numerical comparison

In section 3 the efficiencies are derived for which the proposed median based modified ratio estimators to be performed better than the other usual estimators like, SRSWOR sample mean, ratio estimator, modified ratio estimator, linear regression estimator and median based ratio estimator. Alternatively one has to resort for numerical comparisons to determine the efficiencies of the proposed estimators. In this connection, we have considered three natural populations for assessing the efficiencies of the proposed median based modified ratio estimators with that of the existing estimators. The population 1 and 2 are taken from Daroga Singh and Chaudhary (1986, page no.177), the population 3 is taken from Mukhopadhyay (1998, page no.104). The parameter values and constants computed for the above populations are given in the Table 4.1; the bias for the proposed and existing estimators computed for the three populations are given in the Table 4.2 whereas the mean squared error for the proposed and existing estimators computed for the three populations are given in the Table 4.3.

Parameters	For sample size $n = 3$			For sample size $n = 5$		
	Popln-1	Popln-2	Popln-3	Popln-1	Popln-2	Popln-3
N	34	34	20	34	34	20
N	3	3	3	5	5	5
N_{C_n}	5984	5984	1140	278256	278256	15504
$\bar{Y}$	856.4118	856.4118	41.5	856.4118	856.4118	41.5
$\bar{M}$	747.7223	747.7223	40.2351	736.9811	736.9811	40.0552
M	767.5	767.5	40.5	767.5	767.5	40.5
$\bar{X}$	208.8824	199.4412	441.95	208.8824	199.4412	441.95
β_1	0.8475	1.2383	1.0694	0.8475	1.2383	1.0694
R	4.0999	4.2941	0.0939	4.0999	4.2941	0.0939
R'	1.1158	1.1158	1.0247	1.1158	1.1158	1.0247
θ_1	0.9910	0.9862	0.9963	0.9910	0.9862	0.9963
θ_2	0.9975	0.9982	0.9986	0.9975	0.9982	0.9986
θ_1'	0.9975	0.9964	0.9611	0.9975	0.9964	0.9611
θ_2'	0.9993	0.9995	0.9852	0.9993	0.9995	0.9852
$V(\bar{y})$	163356.4086	163356.4086	27.1254	91690.3713	91690.3713	14.3605
$V(\bar{x})$	6884.4455	6857.8555	2894.3089	3864.1726	3849.248	1532.2812
$V(m)$	101518.7738	101518.7738	26.1307	59396.2836	59396.2836	10.8348
$Cov(\bar{y}, m)$	90236.2939	90236.2939	21.0918	48074.9542	48074.9542	9.0665
$Cov(\bar{y}, \bar{x})$	15061.4011	14905.0488	182.7425	8453.8187	8366.0597	96.7461
ρ	0.4491	0.4453	0.6522	0.4491	0.4453	0.6522

Table 4.1: Parameter values and constants for 3 different populations

Estimators		For sample size $n = 3$			For sample size $n = 5$		
		Popln-1	Popln-2	Popln-3	Popln-1	Popln-2	Popln-3
Existing	$\hat{\bar{Y}}_R$	63.0241	72.9186	0.2015	35.3748	40.9285	0.1067
	$\hat{\bar{Y}}_{RM1}$	61.2517	69.9028	0.1985	34.3800	39.2358	0.1051
	$\hat{\bar{Y}}_{RM2}$	62.5296	72.5220	0.2003	35.0972	40.7059	0.1061
	$\hat{\bar{Y}}_M$	52.0924	52.0924	0.4118	57.7705	57.7705	0.5061
Proposed	$\hat{\bar{Y}}_{SP1}$	51.6035	51.3734	0.3710	57.4176	57.2514	0.4761
	$\hat{\bar{Y}}_{SP2}$	51.9546	51.9989	0.3960	57.6711	57.7031	0.4945

Table 4.2: Bias of the existing and proposed estimators

Estimators		For sample size $n = 3$			For sample size $n = 5$		
		Popln-1	Popln-2	Popln-3	Popln-1	Popln-2	Popln-3
Existing	$\bar{y}$	163356.4086	163356.4086	27.1254	91690.3713	91690.3713	14.3605
	$\hat{\bar{Y}}_R$	155577.8155	161802.8878	18.3261	87324.3215	90818.3961	9.7020
	$\hat{\bar{Y}}_{RM1}$	154615.6994	160103.3428	18.2646	86784.2951	89864.4579	9.6695
	$\hat{\bar{Y}}_{RM2}$	155308.6806	161578.4766	18.3031	87173.2587	90692.4362	9.6899
	$\hat{\bar{Y}}_{lr}$	130408.9222	130964.1249	15.5872	73197.2660	73508.8959	8.2520
	$\hat{\bar{Y}}_M$	88379.0666	88379.0666	11.3372	58356.9234	58356.9234	7.1563
Proposed	$\hat{\bar{Y}}_{SP1}$	88253.6950	88195.0628	10.9255	58257.7340	58211.2376	7.0112
	$\hat{\bar{Y}}_{SP2}$	88343.6455	88355.0109	11.1705	58328.9312	58337.9156	7.0969

Table 4.3: Variance / Mean squared error of the existing and proposed estimators

The percentage relative efficiencies of the proposed estimators with respect to the existing estimators are obtained are obtained by $\mathrm{PRE}(e, p) = \frac{\mathrm{MSE}(e)}{\mathrm{MSE}(p)} * 100$

Estimators	For sample size $n = 3$			For sample size $n = 5$		
	Popln-1	Popln-2	Popln-3	Popln-1	Popln-2	Popln-3
$\bar{y}$	185.10	185.22	248.28	157.39	157.51	204.82
$\hat{\bar{Y}}_R$	176.28	183.46	167.74	149.89	156.02	138.38
$\hat{\bar{Y}}_{RM1}$	175.19	181.53	167.17	148.97	154.38	137.92
$\hat{\bar{Y}}_{RM2}$	175.98	183.21	167.53	149.63	155.80	138.21
$\hat{\bar{Y}}_{lr}$	147.77	148.49	142.67	125.64	126.28	117.70
$\hat{\bar{Y}}_M$	100.14	100.21	103.77	100.17	100.25	102.07

Table 4.4: Percentage Relative Efficiency of Proposed Estimator $\hat{\bar{Y}}_{SP1}$

Estimators	For sample size $n = 3$			For sample size $n = 5$		
	Popln-1	Popln-2	Popln-3	Popln-1	Popln-2	Popln-3
$\bar{y}$	184.91	184.89	242.83	157.20	157.17	202.35
$\hat{\bar{Y}}_R$	176.11	183.13	164.06	149.71	155.68	136.71
$\hat{\bar{Y}}_{RM1}$	175.02	181.20	163.51	148.78	154.04	136.25
$\hat{\bar{Y}}_{RM2}$	175.80	182.87	163.85	149.45	155.46	136.54
$\hat{\bar{Y}}_{lr}$	147.62	148.22	139.54	125.49	126.01	116.28
$\hat{\bar{Y}}_M$	100.04	100.03	101.49	100.05	100.03	100.84

Table 4.5: Percentage Relative Efficiency of Proposed Estimator $\hat{\bar{Y}}_{SP2}$

From the Tables 4.4 and 4.5, it is observed that, the percentage relative efficiencies of the proposed estimators with respect to existing estimators are in general ranging from 100.03 to 248.28. Particularly, the PRE is ranging from 157.17 to 248.28 with SRSWOR sample mean; 136.71 to 183.46 with ratio estimator; 136.25 to 183.21 with modified ratio estimators; 116.28 to 148.49 with linear regression estimator and 100.03 to 103.77 with median based ratio estimator. This shows that the proposed estimators perform better than the existing SRSWOR sample mean, ratio estimator, Modified ratio estimators and linear regression estimators for all the three populations considered here. Further it is observed from the numerical comparisons that the following inequalities:

$$\mathrm{MSE}\left(\hat{\bar{Y}}_{SPj}\right) \leq \mathrm{MSE}\left(\hat{\bar{Y}}_{M}\right) \leq \mathrm{V}\left(\hat{\bar{Y}}_{lr}\right) \leq \mathrm{MSE}\left(\hat{\bar{Y}}_{RMi}\right) \leq \mathrm{MSE}\left(\hat{\bar{Y}}_{R}\right) \leq \mathrm{V}(\bar{y}), i, j = 1,2$$

5. Conclusion

This paper deals with some new median based modified ratio estimators using known correlation coefficient and skewness of the auxiliary variable. The conditions are obtained for which the proposed estimators are more efficient than the existing estimators. Further it is shown that the percentage relative efficiencies of the proposed estimators with respect to existing estimators are ranging from 100.03 to 248.28 for certain natural populations available in the literature. It is usually believed that the linear regression estimator is the best linear unbiased estimator or the optimum estimator for estimating the population mean whenever there exist an auxiliary variable, which is positively and highly correlated with that of the study variable. However it is shown that the proposed median based modified ratio estimators are outperformed not only the ratio and modified ratio estimators but also the linear regression estimator. Hence the proposed median based modified ratio estimators are recommended for solving the practical problems.

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References

1. Cochran, W. G. (1977). Sampling Techniques, Third Edition, Wiley Eastern Limited
2. Kadilar, C. and Cingi, H. (2004). Ratio estimators in simple random sampling, Applied Mathematics and Computation, Vol. 151, p. 893-902.
3. Kadilar, C. and Cingi, H. (2006a). An improvement in estimating the population mean by using the correlation co-efficient, Hacettepe Journal of Mathematics and Statistics, Vol. 35 (1), p. 103-109
4. Kadilar, C. and Cingi, H. (2006b). Improvement in estimating the population mean in simple random sampling, Applied Mathematics Letters, Vol. 19, p. 75-79.
5. Kadilar, C. and Cingi, H. (2009). Advances in Sampling Theory- Ratio Method of Estimation, Bentham Science Publishers.

6. Koyuncu, N. and Kadilar, C. (2009). Efficient estimators for the population mean, Hacettepe Journal of Mathematics and Statistics, Vol. 38(2), p. 217-225.
7. Murthy, M.N. (1967). Sampling Theory and Methods, Statistical Publishing Society, Calcutta, India.
8. Mukhopadhyay, P. (1998). Theory and Methods of Survey Sampling, PHI Learning, 2nd edition, New Delhi.
9. Singh, D. and Chaudhary, F.S. (1986). Theory and Analysis of Sample Survey Designs, New Age International Publisher.
10. Singh, H.P. and Tailor, R. (2003). Use of known correlation co-efficient in estimating the finite population means, Statistics in Transition, Vol. 6 (4), p. 555-560.
11. Singh, H.P. and Tailor, R. (2005). Estimation of Finite Population Mean with Known co-efficient of variation of an auxiliary variable, Statistica, Anno LXV, n.3, p. 301-313.
12. Singh, G.N. (2003). On the improvement of product method of estimation in sample surveys, Journal of Indian Society of Agricultural Statistics 56 (3), p. 267–265.
13. Sisodia, B.V.S. and Dwivedi, V.K. (1981). A Modified Ratio Estimator using coefficient of variation of auxiliary variable, Journal of the Indian Society of Agricultural Statistics, Vol. 33(2), p. 13-18.
14. Subramani, J. (2013). Generalized modified ratio estimator for estimation of the finite population mean, Journal of Modern Applied Statistical Methods, Vol. 12(2), p. 121-155.
15. Subramani, J. and Kumarapandiyan, G. (2012a). Modified Ratio Estimators for population mean using function of Quartiles of auxiliary variable, Bonfring International Journal of Industrial Engineering and Management Science, Vol. 2(2), p. 19-23.
16. Subramani, J. and Kumarapandiyan, G. (2012b). Modified ratio estimators using known median and co-efficient of kurtosis, American Journal of Mathematics and Statistics, Vol. 2(4), p. 95-100.
17. Subramani, J. and Kumarapandiyan, G. (2012c). Estimation of population mean using known median and co-efficient of skewness, American Journal of Mathematics and Statistics, Vol. 2(5), p. 101-107.
18. Subramani, J. and Kumarapandiyan,G. (2013). A new modified ratio estimator of population mean when median of the auxiliary variable is known, Pakistan Journal of Statistics and Operation Research, Vol. 9(2), p. 137-145.
19. Subramani, J. and Prabavathy, G (2014). Median based modified ratio estimators with known quartiles of an auxiliary variable, Journal of Modern Applied Statistical Methods, Vol. 13(1), p. 234-254.
20. Tailor, R. and Sharma, B. (2009). A Modified ratio-cum-product estimator of finite population mean using known coefficient of variation and coefficient of kurtosis, Statistics in Transition-New Series, Vol. 10(1), 15-24.
21. Tin, M. (1965). Comparison of Some Ratio Estimators, Journal of the American Statistical Association, Vol. 60, 294-307.
22. Yan, Z. and Tian, B. (2010). Ratio Method to the mean estimation using co-efficient of skewness of auxiliary variable, ICICA 2010, Part II, CCIS 106, p. 103–111.