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Alternative Ratio - Regression Type Estimator in Simple Random Sampling

Adewara*, A. A.

Department of Statistics, University of Ilorin, Ilorin, Nigeria.

Abstract

In this study, an alternative ratio-regression type estimator was proposed which was compared with Kadilar and Cingi (2004), and Ekaete *et al*. (2014) estimators. This proposed estimator combined classical ratio estimator with our usual regression estimator. The same data set used by Kadilar and Cingi (2004) and Ekaete *et al*. (2014) were also used to determine the efficiency of this alternative ratio-regression type estimator. The finding was that, when $\alpha = 1$, Ekaete *et al*. (2014) was found to be better but at $\alpha \le \sqrt{\frac{(\frac{\bar{X}}{\bar{X}+\rho})^2 c^2{}_y (1-\rho^2)}{(c^2{}_y + c^2{}_x - 2\rho c_y c_x)}}$, this alternative ratio-regression type estimator was said to be more efficient than both Kadilar and Cingi (2004), and Ekaete *et al*. (2014) estimators based on their estimated mean square error (mse).

Keywords: Alternative ratio regression, Combined classical ratio, estimator, bias, mean square error.

1. Introduction

Let N and n be the population and sample sizes respectively, $\bar{X}$ and $\bar{Y}$ be the population means for the auxiliary variable (X) and the variable of interest (Y), $\bar{x}$ and $\bar{y}$ be the sample means based on the sample drawn. Then classically (Cochran, 1977 and Okafor, 2002)

$$\bar{y}_r = \frac{\bar{y}}{\bar{x}} \bar{X}, \quad (1)$$

$$bias(\bar{y}_r) = (\frac{1-f}{n}) \bar{Y} [c^2{}_x - \rho c_x c_y] \quad (2)$$

*Corresponding Author: Adewara, A.A.
Email: aaadewara@gmail.com, aadewara@unilorin.edu.ng

and

$$mse(\bar{y}_r) = (\frac{1-f}{n})\bar{Y}^2[c^2{}_x + c^2{}_y - 2\rho c_x c_y)]. \tag{3}$$

The literature on survey sampling describes a great variety of techniques for using auxiliary information to obtain more efficient estimators. Ratio method of estimation is a good example in this context. If the correlation between the study variable y and the auxiliary variable x is positive (high), the ratio method of estimation is quite effective.

In sample surveys, supplementary information is often used for increasing the precision of estimators (Adewara, 2006; Ogunyinka and Sodipo, 2013; Onyeka, 2012 and Pandey *et al.* , 2011).

Many authors including: Adewara (2015), Solanki *et al*. (2012) and Subramani and Kumarapandiyan (2012) have used auxiliary information for improved estimation of population mean of study variable y.

2. Materials and Methods

On the Kadilar and Cingi (2004) Estimator

Kadilar and Cingi (2004) proposed an estimator, $\bar{y}_{kc} = \frac{\bar{y} + b(\bar{X} - \bar{x})}{\bar{x}}\bar{X}$ and gave its bias and mean square error (mse) respectively as:

$$bias(\bar{y}_{kc}) = (\frac{1-f}{n})\bar{Y}c^2{}_x \tag{4}$$

and

$$mse(\bar{y}_{kc}) = (\frac{1-f}{n})\bar{Y}^2[c^2{}_x + c^2{}_y(1-\rho^2)] , \tag{5}$$

where $f = \frac{n}{N}$.

On Ekaete *et al*. (2014) Estimator

Ekaete *et al*. (2014) suggested an estimator

$$\bar{y}_{ek} = \frac{\alpha\bar{y}(\bar{X} + \rho)}{\bar{x} + \rho} + \frac{\beta[\bar{y} + b(\bar{X} - \bar{x})]\bar{X}}{\bar{x}} \tag{6}$$

with an

$$mse(\bar{y}_{eh}) = (\frac{1-f}{n})\bar{Y}^2[c^2{}_y(1-\rho^2)] \quad . \tag{7}$$

On the proposed alternative ratio-regression type estimator

The classical ratio estimator used in this study is defined as $\bar{y}_{r^*} = \alpha(\frac{\bar{y}}{\bar{x}})(\bar{X}+\rho)$ while our traditional regression estimator used is defined as: $\bar{y}_{reg} = \beta[\bar{y}+b(\bar{X}-\bar{x})]$ such that $\alpha+\beta=1$. Their biases and mean square errors are given respectively as:

$$bias(\bar{y}_r) = (\frac{1-f}{n})\bar{Y}[c^2{}_x - \rho c_x c_y], \tag{8}$$

$$mse(\bar{y}_r) = (\frac{1-f}{n})\bar{Y}^2[c^2{}_x + c^2{}_y - 2\rho c_x c_y)], \tag{9}$$

$$bias(\bar{y}_{reg}) = 0, \tag{10}$$

and

$$mse(\bar{y}_{reg}) = (\frac{1-f}{n})\bar{Y}^2[c^2{}_y(1-\rho^2)]. \tag{11}$$

The alternative ratio-regression type estimator is given as:

$$\bar{y}_{aa^*} = \alpha(\frac{\bar{y}}{\bar{x}})(\bar{X}+\rho) + \beta[\bar{y}+b(\bar{X}-\bar{x})], \tag{12}$$

linear combination of classical ratio estimator, $\bar{y}_{r^*}$, and the traditional regression estimator, $\bar{y}_{reg}$, where $\bar{x} = \bar{X}(1+\Delta_{\bar{x}})$, $\bar{y} = \bar{Y}(1+\Delta_{\bar{y}})$, $\Delta_{\bar{y}} = \frac{\bar{y}-\bar{Y}}{\bar{Y}}$, $\Delta_{\bar{x}} = \frac{\bar{x}-\bar{X}}{\bar{X}}$ such that $|\Delta_{\bar{y}}| < 1$ and $|\Delta_{\bar{x}}| < 1$.

The bias and mean square error of this alternative ratio-regression type estimator, $\bar{y}_{aa^*}$ are respectively given as:-

$$bias(\bar{y}_{aa^*}) = (\frac{1-f}{n})(\frac{\bar{X}+\rho}{\bar{X}})\alpha\bar{Y}(c^2{}_x - \rho c_x c_y) \tag{13}$$

and

$$mse(\bar{y}_{aa^*}) = (\frac{1-f}{n})(\frac{\bar{X}+\rho}{\bar{X}})^2\alpha^2\bar{Y}^2[c^2{}_x + c^2{}_y - 2\rho c_x c_y], \tag{14}$$

provided

$$\frac{\bar{X}+\rho}{\bar{X}} \geq 1. \quad (15)$$

The proof of (13) and (14) are as shown below:

Derivation of Bias and Mean Square Error of $\bar{y}_{aa}$.

Let

$\bar{y}_{aa^*} = \alpha(\frac{\bar{y}}{\bar{x}})(\bar{X}+\rho)+\beta[\bar{y}+b(\bar{X}-\bar{x})]$, where, $\bar{x} = \bar{X}(1+\Delta_{\bar{x}})$, $\bar{y} = \bar{Y}(1+\Delta_{\bar{y}})$,

$\Delta_{\bar{y}} = \frac{\bar{y}-\bar{Y}}{\bar{Y}}$, $\Delta_{\bar{x}} = \frac{\bar{x}-\bar{X}}{\bar{X}}$ such that $|\Delta_{\bar{y}}| < 1$ and $|\Delta_{\bar{x}}| < 1$ as earlier defined.

Therefore, using power series expansion

$$\bar{y}_{aa^*} = \alpha(\frac{\bar{y}}{\bar{x}})(\bar{X}+\rho)+\beta[\bar{y}+b(\bar{X}-\bar{x})] = \alpha(\frac{\bar{y}}{\bar{x}})(\bar{X}+\rho)+(1-\alpha)[\bar{y}+b(\bar{X}-\bar{x})],$$

$$= \alpha(\frac{\bar{Y}(1+\Delta_{\bar{y}})}{\bar{X}(1+\Delta_{\bar{x}})})(\bar{X}+\rho)+(1-\alpha)[\bar{Y}(1+\Delta_{\bar{y}})+b(\bar{X}-\bar{X}(1+\Delta_{\bar{x}}))],$$

$$= \alpha(\frac{\bar{Y}}{\bar{X}})(1+\Delta_{\bar{y}})(1+\Delta_{\bar{x}})^{-1}(\bar{X}+\rho)+\bar{Y}(1+\Delta_{\bar{y}})+b\bar{X}-b\bar{X}-b\bar{X}\Delta_{\bar{x}}-\alpha\bar{Y}-\alpha\Delta_{\bar{y}}+$$
$$\alpha b\bar{X}-\alpha b\bar{X}-\alpha b\Delta_{\bar{x}}$$

$$= \alpha(\frac{\bar{Y}}{\bar{X}})(\bar{X}+\rho)(1+\Delta_{\bar{y}})(1-\Delta_{\bar{x}}+\Delta^2{}_{\bar{x}})+\bar{Y}+\bar{Y}\Delta_{\bar{y}}-b\bar{X}\Delta_{\bar{x}}-\alpha\bar{Y}-\alpha\Delta_{\bar{y}}-\alpha b\Delta_{\bar{x}},$$

$$= \alpha\bar{Y}(\frac{\bar{X}+\rho}{\bar{X}})(1+\Delta_{\bar{y}})(1-\Delta_{\bar{x}}+\Delta^2{}_{\bar{x}})+\bar{Y}+\bar{Y}\Delta_{\bar{y}}-b\Delta_{\bar{x}}-\alpha\bar{Y}-\alpha\Delta_{\bar{y}}-\alpha b\Delta_{\bar{x}},$$

$$= \alpha\bar{Y}k(1+\Delta_{\bar{y}})(1-\Delta_{\bar{x}}+\Delta^2{}_{\bar{x}})+\bar{Y}+\bar{Y}\Delta_{\bar{y}}-b\Delta_{\bar{x}}-\alpha\bar{Y}-\alpha\Delta_{\bar{y}}-\alpha b\Delta_{\bar{x}},$$

where $k = (\frac{\bar{X}+\rho}{\bar{X}})$,

$$= \alpha\bar{Y}k(1-\Delta_{\bar{x}}+\Delta^2{}_{\bar{x}}+\Delta_{\bar{y}}-\Delta_{\bar{x}}\Delta_{\bar{y}}+\Delta^2{}_{\bar{x}}\Delta_{\bar{y}})+\bar{Y}+\bar{Y}\Delta_{\bar{y}}-b\Delta_{\bar{x}}-\alpha\bar{Y}-\alpha\Delta_{\bar{y}}-\alpha b\Delta_{\bar{x}},$$

$$Bias(\bar{y}_{aa^*}) = E[((\alpha\bar{Y}k(1-\Delta_{\bar{x}}+\Delta^2{}_{\bar{x}}+\Delta_{\bar{y}}-\Delta_{\bar{x}}\Delta_{\bar{y}}+\Delta^2{}_{\bar{x}}\Delta_{\bar{y}}))+\bar{Y}+\bar{Y}\Delta_{\bar{y}}-b\Delta_{\bar{x}}-\alpha\bar{Y}$$
$$-\alpha\Delta_{\bar{y}}-\alpha b\Delta_{\bar{x}})-\bar{Y}],$$

$$Bias(\bar{y}_{aa^*}) = E[(\alpha\bar{Y}k-\alpha\bar{Y}k\Delta_{\bar{x}}+\alpha\bar{Y}k\Delta^2{}_{\bar{x}}+\alpha\bar{Y}k\Delta_{\bar{y}}-\alpha\bar{Y}k\Delta_{\bar{x}}\Delta_{\bar{y}}+\alpha\bar{Y}k\Delta^2{}_{\bar{x}}\Delta_{\bar{y}}+\bar{Y}+$$
$$\bar{Y}\Delta_{\bar{y}}-b\Delta_{\bar{x}}-\alpha\bar{Y}-\alpha\Delta_{\bar{y}}-\alpha b\Delta_{\bar{x}})-\bar{Y}],$$

$Bias(\bar{y}_{aa^*}) = E(\alpha\bar{Y}k\Delta^2{}_{\bar{x}} - \alpha\bar{Y}k\Delta_{\bar{x}}\Delta_{\bar{y}})$.

Let, $E(\Delta_{\bar{y}}) = E(\Delta_{\bar{x}}) = 0, E(\Delta_{\bar{x}}{}^2) = \frac{S^2{}_x}{\bar{X}^2} = c^2{}_x, E(\Delta_{\bar{y}}{}^2) = \frac{S^2{}_y}{\bar{Y}^2} = c^2{}_y$ and

$E(\Delta_x\Delta_y) = \frac{S_{xy}}{\bar{X}\bar{Y}} = \rho c_x c_y$. Then

$$Bias(\bar{y}_{aa^*}) = \frac{(1-f)}{n}\alpha\bar{Y}k[c^2{}_x - \rho c_x c_y),$$

$$bias(\bar{y}_{aa^*}) = (\frac{1-f}{n})(\frac{\bar{X}+\rho}{\bar{X}})\alpha\bar{Y}(c^2{}_x - \rho c_x c_y)$$ (as in eq. (13) above),

$$Mse(\bar{y}_{aa^*}) = E[(\alpha\bar{Y}k((1-\Delta_{\bar{x}} + \Delta^2{}_{\bar{x}} + \Delta_{\bar{y}} - \Delta_{\bar{x}}\Delta_{\bar{y}} + \Delta^2{}_{\bar{x}}\Delta_{\bar{y}}) + \bar{Y} + \bar{Y}\Delta_{\bar{y}} - b\Delta_{\bar{x}} - \alpha\bar{Y} - \alpha\Delta_{\bar{y}} - \alpha b\Delta_{\bar{x}}) - \bar{Y}]^2,$$

$$Mse(\bar{y}_{aa^*}) = E(\alpha\bar{Y}k(\Delta_{\bar{y}} - \Delta_{\bar{x}}))^2,$$

$$Mse(y_{aa^*}) = (\frac{1-f}{n})(\frac{\bar{X}+\rho}{\bar{X}})^2\alpha^2\bar{Y}^2[c^2{}_x + c^2{}_y - 2\rho c_x c_y]$$, (as in eq. (14) above).

COMPARISON

Efficiency of $\bar{y}_{aa^*}$ over $\bar{y}_{kc}$.

The proposed alternative ratio-regression type estimator, $\bar{y}_{aa^*}$, is said to be better and more efficient than Kadilar and Singh (2004) estimator, $\bar{y}_{kc}$, whenever $mse(\bar{y}_{aa^*}) < mse(\bar{y}_{kc})$. That is,

$$(\frac{1-f}{n})(\frac{\bar{X}+\rho}{\bar{X}})^2\alpha^2\bar{Y}^2[c^2{}_x + c^2{}_y - 2\rho c_x c_y] < (\frac{1-f}{n})\bar{Y}^2[c^2{}_x + c^2{}_y(1-\rho^2)]$$ provided

$$\alpha \le \sqrt{\frac{(\frac{\bar{X}}{\bar{X}+\rho})^2[c^2{}_x + c^2{}_y(1-\rho^2)]}{(c^2{}_y + c^2{}_x - 2\rho c_y c_x)}}. \qquad (16)$$

Efficiency of $\bar{y}_{aa^*}$ over $\bar{y}_{ek}$.

The proposed alternative ratio-regression type estimator, $\bar{y}_{aa^*}$, is said to be better and more efficient than Ekaete *et al*. (2014) estimator, $\bar{y}_{ek}$, whenever $mse(\bar{y}_{aa^*}) < mse(\bar{y}_{ek})$. That is,

$$(\frac{1-f}{n})(\frac{\overline{X}+\rho}{\overline{X}})^2\alpha^2\overline{Y}^2[c^2{}_x+c^2{}_y-2\rho c_x c_y]<(\frac{1-f}{n})\overline{Y}^2[c^2{}_y(1-\rho^2)]\ \text{provided,}$$

$$\alpha\le\sqrt{\frac{(\frac{\overline{X}}{\overline{X}+\rho})^2c^2{}_y(1-\rho^2)}{(c^2{}_y+c^2{}_x-2\rho c_y c_x)}}\ . \qquad (17)$$

3. Results and Discussion

Data used

Four data sets used by Kadilar and Singh (2004), and Ekaete *et al*. (2014) are also used here to compare the efficiency of this alternative ratio-regression type estimator with Kadilar and Singh (2004), and Ekaete *et al*. (2014) estimators.

Table 1: Data used

Population I:- Kadilar and Cingi (2004).

$c_x=2,\ c_y=15,\ \overline{X}=25,\ \overline{Y}=500,\ \rho=0.90,$ n = 50, N = 200 and $\frac{\overline{X}+\rho}{\overline{X}}=1.03$.

Population II:- Kadilar and Cingi (2003).

$c_x=2.02,\ c_y=4.18,\ \overline{X}=24375.59,\ \overline{Y}=1536.77,\ \rho=0.82,$ n = 20, N = 106 and $\frac{\overline{X}+\rho}{\overline{X}}=1.00000336.$

Population III:- Murthy (1967).

$c_x=0.7507,\ c_y=0.3542,\ \overline{X}=11.2624,\ \overline{Y}=51.8264,\ \rho=0.9413,$ n = 20, N = 80 and $\frac{\overline{X}+\rho}{\overline{X}}=1.08358.$

Population IV:- Das (1988).

$c_x=1.6198,\ c_y=1.4451,\ \overline{X}=25.111,\ \overline{Y}=39.068,\ \rho=0.7213,$ n = 48, N = 278 and $\frac{\overline{X}+\rho}{\overline{X}}=1.02872446.$

Results

The estimates obtained using the above data sets are shown in Table 2 below:

Table 2:- Bias and Mean Square Error obtained on $\bar{y}_{aa^*}$, $\bar{y}_{kc}$ and $\bar{y}_{ek}$

Population	I	II	III	IV
bias($\bar{y}_{kc}$)	-167.512	254.3749	1.095255	1.766793
bias($\bar{y}_{aa^*}$)	-178.70	-177.2624	0.6597	0.6479
$\sqrt{\frac{(\frac{\bar{X}}{\bar{X}+\rho})^2 c^2{}_y(1-\rho^2)}{(c^2{}_y+c^2{}_x-2\rho c_y c_x)}}$	0.4771	0.8619	0.2542	0.8435
mse($\bar{y}_{kc}$)	775,312.50	939,289.60	58.20311	95.38072
mse($\bar{y}_{aa^*}$) when				
α =1.0	704,350.0	738,242.23	22.2844	37.1750
0.9	570,523.50	597,976.2063	18.0504	30.1118
0.8	450,784	**472,475**	14.2620	**23.7920**
0.7	345,131.50	**361,738.6927**	10.9194	**18.2158**
0.6	253,566	**265,767.2028**	8.0224	**13,383**
0.5	176,087.50	**184,560.5575**	5.5711	**9.1750**
0.4	**112,696**	**118,118.7568**	3.5655	**5.9480**
0.3	**63,391.50**	**66,441.8007**	2.0056	**3.3458**
0.2	**28,174**	**29,529.6892**	**0.8914**	**1.4870**
0.1	**7,043.50**	**7,382.4223**	**0.2228**	**0.3718**
mse($\bar{y}_{ek}$)	160,312.50	548,359.8951	1.4348	26.3544
$(\frac{\bar{X}+\rho)}{\bar{X}})$	1.07329	1.0000336	1.0836	1.0287
$(\frac{\bar{X}+\rho)}{\bar{X}})^2$	1.060	1.00006728	1.1741889	1.05827402

Discussion

From the estimates in the Table 2 above for:

(a). when $\alpha = 1$,

(i). For Population I, $mse(\bar{y}_{kc}) = 775{,}312.50$, $mse(\bar{y}_{aa^*}) = 704{,}350$ and $mse(\bar{y}_{ek}) = 160{,}312.50$. Hence, $mse(\bar{y}_{ek}) < mse(\bar{y}_{aa^*}) < mse(\bar{y}_{kc})$.

(ii). For Population II, $mse(\bar{y}_{kc}) = 939{,}289.60$, $mse(\bar{y}_{aa^*}) = 738{,}242.23$ and $mse(\bar{y}_{ek}) = 548{,}359.8951$. Hence, $mse(\bar{y}_{ek}) < mse(\bar{y}_{aa^*}) < mse(\bar{y}_{kc})$.

(iii). For Population III, $mse(\bar{y}_{kc}) = 58.20311$, $mse(\bar{y}_{aa^*}) = 22.2844$ and $mse(\bar{y}_{ek}) = 1.4340$. Hence, $mse(\bar{y}_{ek}) < mse(\bar{y}_{aa^*}) < mse(\bar{y}_{kc})$.

(iv). For Population IV, $mse(\bar{y}_{kc}) = 95.38072$, $mse(\bar{y}_{aa^*}) = 37.1750$ and $mse(\bar{y}_{ek}) = 26.3544$. Hence, $mse(\bar{y}_{ek}) < mse(\bar{y}_{aa^*}) < mse(\bar{y}_{kc})$.

(b). When $\alpha \le \sqrt{\dfrac{(\frac{\bar{X}}{\bar{X}+\rho})^2 c^2{}_y (1-\rho^2)}{(c^2{}_y + c^2{}_x - 2\rho c_y c_x)}}$,

(i). For Population I, $\alpha \le 0.4771$, $mse(\bar{y}_{aa^*}) = 112{,}696$, $mse(\bar{y}_{kc}) = 775{,}312.50$, and $mse(\bar{y}_{ek}) = 160{,}312.50$. Hence, $mse(\bar{y}_{aa^*}) < mse(\bar{y}_{ek}) < mse(\bar{y}_{kc})$.

(ii). For Population II, $\alpha \le 0.8619$, $mse(\bar{y}_{aa^*}) = 472{,}475$, $mse(\bar{y}_{kc}) = 939{,}289.60$, and $mse(\bar{y}_{ek}) = 548{,}359.8951$. Hence, $mse(\bar{y}_{aa^*}) < mse(\bar{y}_{ek}) < mse(\bar{y}_{kc})$.

(iii). For Population III, $\alpha \le 0.2542$, $mse(\bar{y}_{aa^*}) = 0.8914$, $mse(\bar{y}_{kc}) = 58.20311$, and $mse(\bar{y}_{ek}) = 1.4340$. Hence, $mse(\bar{y}_{aa^*}) < mse(\bar{y}_{ek}) < mse(\bar{y}_{kc})$.

(iv). For Population IV, $\alpha \le 0.8435$, $mse(\bar{y}_{aa^*}) = 23.7920$, $mse(\bar{y}_{kc}) = 95.38072$, and $mse(\bar{y}_{ek}) = 26.3544$. Hence, $mse(\bar{y}_{aa^*}) < mse(\bar{y}_{ek}) < mse(\bar{y}_{kc})$.

4. Conclusion

Therefore, from all the estimates obtained above, at $\alpha = 1$, Ekaete *et al*. (2014) was found to be better but when $\alpha \le \sqrt{\dfrac{(\frac{\bar{X}}{\bar{X}+\rho})^2 c^2{}_y (1-\rho^2)}{(c^2{}_y + c^2{}_x - 2\rho c_y c_x)}}$, the alternative ratio-regression type estimator was said to be more efficient than both Kadilar and Cingi (2004), and Ekaete *et al*. (2014) estimators based on their estimated mean square error (mse). Hence, the alternative ratio-regression type estimator, $\bar{y}_{aa^*}$, is recommended for usage in sample survey.

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