

An Estimator for Population Mean Using Power Transformation and Auxiliary Information

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Abstract

In this paper we have suggested a family of ratio-cum product estimator when the population coefficient of variation (C_x) alongwith population means (\bar{X}) of the auxiliary variable x is known in advance. Its bias and variance to the first degree of approximation are obtained. For an appropriate weight 'w' and a good range of α -values, it is shown that the suggested estimator is more efficient than the set of estimators viz. usual unbiased estimator, usual ratio and product estimators, Sisodia and Dwivedi's⁵ estimator, Bansal and Singh's¹ estimator, Chakraborty's² type estimator, Vos's⁸ type estimator and Sahai and Ray⁴ type estimator, some of which are in fact particular members of it.

Key words: Finite population, Study variable, Auxiliary variable, Bias, Variance.

1. Introduction

It is well that the use of auxiliary variable (x) at the estimation stage improve of the population mean (\bar{Y}) of the study variable (y). Out of many ratio, product and regression estimator's are good examples in this context.

Let $U = \{U_1, U_2, \dots, U_n\}$ be a finite population of N units and y be the study variable which takes values x_i on the i^{th} unit, ($i = 1, 2, \dots, N$). Let (\bar{Y}, \bar{X}) be the population

means of y and x respectively. For estimating \bar{Y} , a simple random sample of size n is drawn without replacement (WOR) from the population U . When the population mean \bar{X} of x is known, the classical ratio and product estimators of population mean \bar{Y} determined by the intuitively plausible relations are respectively given by

$$\bar{y}_R = \bar{y} \frac{\bar{X}}{\bar{x}} \quad (1.1)$$

and

$$\bar{y}_p = \bar{y} \frac{\bar{x}}{\bar{X}} \quad (1.2)$$

where $\bar{y} = (1/n) \sum_{i=1}^n y_i$ and $\bar{x} = (1/n) \sum_{i=1}^n x_i$ are the sample means of y and x respectively based on n observations.

Utilizing information on known population coefficient of variation (C_x) alongwith known population mean (\bar{X}) of auxiliary variable x , Sisodia and Dwivedi⁵, Pandey and Dubey³ suggested the following modified ratio and product estimators for as

$$\bar{y}_R^{(m)} = \bar{y} \frac{(\bar{X} + C_x)}{(\bar{x} + C_x)} \quad (1.3)$$

and

$$\bar{y}_P^{(m)} = \bar{y} \frac{(\bar{X} + C_x)}{(\bar{X} + C_x)} \quad (1.4)$$

By applying power transformation on $\bar{y}_R^{(m)}$ and $\bar{y}_P^{(m)}$, Bansal and Singh (1992-93) proposed a modified estimator for \bar{Y} as

$$\bar{y}_B = \bar{y} \left(\frac{\bar{X} + C_x}{\bar{x} + C_x} \right)^a, \quad (1.5)$$

where α is a scalar obtained from a pilot survey, past data or experience. Such an estimator for \bar{Y} has been considered earlier by Srivastava⁷ when \bar{X} is known alone.

The variance of \bar{y} is given by

$$V(\bar{y}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 C_y^2, \quad (1.6)$$

To the first degree of approximation, the variances of \bar{y}_R , \bar{y}_P , $\bar{y}_R^{(m)}$ and $\bar{y}_P^{(m)}$ are respectively given by

$$V(\bar{y}_R) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + C_x^2 (1 - 2C)], \quad (1.7)$$

$$V(\bar{y}_P) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + C_x^2 (1 + 2C)], \quad (1.8)$$

$$V(\bar{y}_R^{(m)}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + \theta C_x^2 (\theta - 2C)], \quad (1.9)$$

$$V(\bar{y}_P^{(m)}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + \theta C_x^2 (\theta + 2C)], \quad (1.10)$$

$$V(\bar{y}_B^{(m)}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + \alpha \theta C_x^2 (\alpha \theta + 2C)], \quad (1.11)$$

where $\theta = \frac{\bar{X}}{\bar{x} + C_x}$, $C = \rho C_y / C_x$, $C_y = S_y / \bar{y}$,

$$C_x = S_x / \bar{x},$$

$$\rho = S_{xy} / (S_y S_x), S_{xy} = \frac{1}{(n-1)} \sum_{i=1}^N (x_i - \bar{X})(y_i - \bar{Y})$$

$$S_y^2 = \frac{1}{(n-1)} \sum_{i=1}^N (y_i - \bar{Y})^2$$

$$S_x^2 = \frac{1}{(n-1)} \sum_{i=1}^N (x_i - \bar{X})^2$$

The objective of this paper is to suggest a family of estimators of \bar{Y} and analyze its properties.

2. Proposed Class of Estimator :

Motivated by Sisodia and Dwivedi^{5,6} we suggest a family of estimators of \bar{Y} as

$$\bar{y}_w = (1-w)\bar{y} + w\bar{y}\left(\frac{\bar{X} + C_X}{\bar{X}}\right)^\alpha \quad (2.1)$$

where w and α are some appropriate constant. For $\alpha > 0$, \bar{y}_w is ratio-type estimator and for $\alpha < 0$, \bar{y}_w is product type estimator, we observe that the estimator reduces to a set of known estimator:

$$\bar{y}_w = \left\{ \bar{y}, \bar{y}_R^{(m)}, \bar{y}_P^{(m)}, \bar{y}_B^{(m)}, \bar{y}_w^{(1)}, \bar{y}_w^{(2)}, \bar{y}_w^{(3)} \right\} \text{ as follows:}$$

(i) Usual unbiased estimator

$$\bar{y}_w \rightarrow \bar{y} \text{ for } \alpha = 0 \text{ (or } w = 0)$$

(ii) Sisodia and Dwivedi's⁵ estimator

$$\bar{y}_w \rightarrow \bar{y}_R^{(m)} \text{ for } \alpha = 1, w = 1$$

(iii) Pandey and Dubey's³ estimator

$$\bar{y}_w \rightarrow \bar{y}_P^{(m)} \text{ for } \alpha = -1, w = 1$$

(iv) Bansal and Singh's¹ estimator

$$\bar{y}_w \rightarrow \bar{y}_B \text{ for } w = 1$$

(v) Chakrabort's² and Vos's⁸ type estimators

$$\bar{y}_w^{(1)} = (1-w)\bar{y} + w\bar{y}\left(\frac{\bar{X} + C_X}{\bar{X}}\right), \text{ for } \alpha=1$$

(vi) Vos's⁸ -type estimator

$$\bar{y}_w^{(2)} = (1-w)\bar{y} + w\bar{y}\left(\frac{\bar{X} + C_X}{\bar{X}}\right), \text{ for } \alpha=1$$

(vii) Sahai and Ray⁴ -type estimator

$$\bar{y}_w^{(3)} = \bar{y} \left[2 - \left(\frac{\bar{X} + C_X}{\bar{X}} \right)^\alpha \right], \text{ for } w=-1,$$

$$\alpha = -\alpha$$

The estimator is a biased one. The bias and variances of \bar{y}_w are derived in section 3. The estimator is compared with other estimators in section 4.

3. Bias and variance :

To the first degree of approximation, the bias and variance of \bar{y}_w are respectively given by

$$B(\bar{y}_w) = w \alpha \theta \bar{Y} \left(\frac{1}{n} - \frac{1}{N} \right) \left\{ \frac{(\alpha+1)}{2} \theta - C \right\} C_X^2 \quad (3.1)$$

and

$$V(\bar{y}_w) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_Y^2 + w \alpha \theta C_X^2 (w \alpha \theta - 2C)] \quad (3.2)$$

If follows from (3.1) that bias of \bar{y}_w are as

follows:

$$B(\bar{y}_w)=0 \Rightarrow \frac{(\alpha+1)\theta}{2} - C = 0 \Rightarrow \alpha = \frac{(2C-\theta)}{\theta} \quad (3.3)$$

The optimum values of w and α which minimizes the variance of \bar{y}_w are as follows:

$$\left. \begin{aligned} w_0 &= \frac{C}{\alpha\theta} \\ \alpha_0 &= \frac{C}{w\theta} \end{aligned} \right\} \quad (3.4)$$

We note from (3.4) that the optimum values of w and α can not uniquely be determined. However, the optimum values of α can be obtained for a given value of w which can be appropriately fixed in advance as being weight. Thus, if we substitute the optimum value of α for a given value of w in (3.2), we get

$$\min.V(\bar{y}_w) = \left(\frac{1}{n} - \frac{1}{N} \right) S_y^2 (1 - \rho^2) \quad (3.5)$$

which is the approximate variance of the usual regression estimator $\bar{y}_{lr} = \bar{y} + \hat{\beta}(\bar{X} - \bar{x})$,

$\hat{\beta} = \frac{S_{xy}}{S_x^2}$ is the sample estimate of population regression coefficient β of y on x . The expression for $\min.V(\bar{y}_w)$ in (3.5) implies that the estimator \bar{y}_w will always be more efficient

than the set of estimators \bar{y}_w' at α_0 . Nevertheless, we shall further determine a range of α -values for which is estimator \bar{y}_w will have lesser

variance than that of \bar{y}_w' .

It is observed that the estimators in \bar{y}_w' are particular member of \bar{y}_w , therefore, from (3.2) we get at once variance of \bar{y}_w' as follows:

$$\begin{aligned} V(\bar{y}_w') &= V[\bar{y}_w]; \text{ according to different values of } \alpha \text{ and } w \text{ given in from (i) to (vii)} \\ &= [V(\bar{y}), V(\bar{y}_R^{(m)}), V(\bar{y}_P^{(m)}), V(\bar{y}_B^{(m)}), \\ &\quad V(\bar{y}_w^{(1)}), V(\bar{y}_w^{(2)}), V(\bar{y}_w^{(3)})] \end{aligned}$$

4. Comparison of with Other Comptetors :

It follows from (1.6), (1.9), (1.10) and (3.2) that the proposed estimator \bar{y}_w is more efficient than \bar{y} , $y_R^{(m)}$, $y_P^{(m)}$ and y_n if

$$|\alpha - \alpha_0| < |\alpha_0| \quad (4.1)$$

$$|\alpha - \alpha_0| < \left| \alpha_0 - \frac{1}{w} \right| \quad (4.2)$$

$$|\alpha - \alpha_0| < \left| \alpha_0 + \frac{1}{w} \right| \quad (4.3)$$

and

$$|\alpha - \alpha_0| < \left| \frac{\alpha_0(w-1)}{(w+1)} \right| \quad (4.4)$$

hold true respectively.

To compare \bar{y}_w with $y_w^{(1)}$, $y_w^{(2)}$ and $y_w^{(3)}$, we write the variances of $y_w^{(1)}$, $y_w^{(2)}$ and $y_w^{(3)}$

upto first order of approximation, respectively as

$$V(y_w^{(1)}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + w\theta C_x^2 (w\theta - 2C)] \quad (4.5)$$

$$V(y_w^{(2)}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + w\theta C_x^2 (w\theta - 2C)] \quad (4.6)$$

$$\text{and } V(y_w^{(3)}) = \left(\frac{1}{n} - \frac{1}{N} \right) \bar{Y}^2 [C_y^2 + \alpha\theta C_x^2 (\alpha\theta - 2C)] \quad (4.7)$$

From (3.2), (4.5), (4.6) and (4.7) we note that the suggested estimator \bar{y}_w is more precise than $y_w^{(1)}$, $y_w^{(2)}$ and $y_w^{(3)}$ if

$$|\alpha - \alpha_0| < |\alpha_0 - 1| \quad (4.8)$$

$$|\alpha - \alpha_0| < |\alpha_0 + 1| \quad (4.9)$$

and

$$|\alpha - \alpha_0| < \left| \frac{\alpha_0(w-1)}{(w+1)} \right| \quad (4.10)$$

hold good respectively.

From (3.2) and (1.7) we noted that $V(\bar{y}_w) < V(\bar{y}_R)$ if

$$|\alpha - \alpha_0| < \left| \alpha_0 - \frac{1}{w\theta} \right| \quad (4.11)$$

Further from (3.2) and (1.8), we note that the suggested estimator \bar{y}_w is more efficient than classical product estimator \bar{y}_p if

$$|\alpha - \alpha_0| < \left| \alpha_0 + \frac{1}{w\theta} \right| \quad (4.12)$$

For a given value of w , the difference between α and the optimum value α_0 in inequalities (4.1)-(4.4), (4.8), (4.9), (4.10), (4.11) and (4.12) provide quite a good range of α -values in order to have the estimator \bar{y}_w more efficient than \bar{y}_w' .

It is to be noted that the optimum value α_0 of α is a function of C , θ and w , it may be positive or negative depending upon the sign of correlation coefficient ' ρ '. In practice, with a good guess of ' C ' obtained through pilot survey, past data or experience gathered in due course of time, and an appropriate weight of w , an optimum value of α fairly very close to its true value α_0 can be obtained. It is pointed out in Sahai and Ray⁴ that when good (specific) gives of C is not available we may still have more information about the range of C , e.g. $C_1 \leq C \leq C_2$ which is more realistic than a specific gives about C . However, in case a good given value of ' C ' is not known, the optimum values of α for different value of C , θ and w can be computed.

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