

An Efficient Predictive Approach to Estimation in Two-phase Sampling

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Abstract: Agrawal and Jain [1] employed a predictive framework to examine the predictive character of ratio, ratio-type and regression estimators in two-phase sampling. In this paper, an efficient predictive estimator, which is the fountainhead of a family of widely used estimators in two-phase sampling, is proposed. The newly proposed estimator has been shown to excel its competing estimators provided a weighting factor is appropriately chosen. In the absence of knowledge of the optimum weighting factor, performance-sensitivity of the proposed estimator has been carried out.

Keywords: Efficient predictive estimator in two-phase sampling; performance-sensitivity; ratio, ratio-type and regression estimators in two-phase sampling;

I. Introduction

In the ratio method of estimation, we, with a view to obtaining more efficient estimators of the population mean of the survey variable y , a known and closely related auxiliary variable x . However, when the population mean of x is not available, we invoke the technique known as two-phase sampling or double sampling. This technique essentially consists in selecting a large sample in the first phase for collecting information on x , followed by a selection of a subsample from the first-phase sample in the second phase for measuring y .

Consider a population of N units arbitrarily labelled $1, 2, \dots, N$ having mean and mean square denoted by (\bar{Y}, S_y^2) for the y -variable and (\bar{X}, S_x^2) for the x -variable, the respective measurements on the y and the x variables for the j th unit being denoted by y_j and $x_j, j=1, 2, \dots, N$. Let n' and n be the sample sizes in the first and the second phases, respectively, drawn according to the method of simple random sampling without replacement. Further, let \bar{x}' and \bar{x} be the means of auxiliary variable x based on n' and n units, respectively, and \bar{y} be the mean of the survey variable y based on n units. Then, the usual ratio-type estimator in two-phase sampling is given by

$$\bar{y}_{rd} = \frac{\bar{y}}{\bar{x}} \bar{x}' \quad (1.1)$$

Agrawal and Jain [2] have shown that \bar{y}_{rd} is predictive in character.

For this purpose, they have split the population total Y in the following form:

$$Y = \sum_{j \in s_2} y_j + \sum_{j \in s_1 \bar{s}_2} y_j + \sum_{j \in \bar{s}_1} y_j \quad (1.2)$$

where s_1 and s_2 denote the first phase and the second phase samples,

respectively, \bar{s}_1 and \bar{s}_2 being their respective complements. The first component of right side of (1.2) being exactly known, each y_j in the segments $s_1 \bar{s}_2$ and \bar{s}_1 , in keeping with the sampling situation at hand, is predicted by means of $(\bar{y}/\bar{x})x_j$ and $(\bar{y}/\bar{x})\bar{x}'$, respectively. Although, this approach adopted by Agrawal and Jain is quite justifiable and intuitively appealing, there is need to generalize the same as regards the prediction of each y_j in $s_1 \bar{s}_2$ and \bar{s}_1 . In a practical situation, it would be ideal to utilize, for prediction purposes, the available information on the main and the auxiliary variables to form suitably weighted predictors for the x -observed segment $s_1 \bar{s}_2$ and the completely non-surveyed (unobserved) segment \bar{s}_1 . It is in the light of this background that we, in the following section, come up with an efficient predictive estimator in two-phase sampling.

II. An Efficient Predictive Estimator in Two-phase Sampling

Since no information on y has been collected in respect of the segments $s_1 \bar{s}_2$ and \bar{s}_1 , it is clear from (1.2) that the population total Y can be estimated if each y_j in these segments is appropriately predicted. Since the auxiliary information is fully available in the segment $s_1 \bar{s}_2$ as per the procedure of two-phase sampling, an apparently broad-based sensible predictor (employing two potential predictors) of y_j in $s_1 \bar{s}_2$ that we propose is

$$\hat{y}_j = \alpha \frac{\bar{y}}{\bar{x}} x_j + (1 - \alpha) \bar{y}, \quad j \in s_1 \bar{s}_2 \quad (2.1)$$

where α is a weight which might be preassigned or might depend on quantities estimated from the sample. In this context, it would be apt to point out that, while \bar{y} is the mean for the segment s_2 , the quantity $(\bar{y}/\bar{x})x_j$ is the usual

predictor for $y_j(j \in s_1 \bar{s}_2)$, see Agrawal and Jain [1]. As regards the non-surveyed segment \bar{s}_1 , a plausible weighted predictor would then be

$$\hat{y}_j = \alpha \frac{\bar{y}}{\bar{x}} \bar{x}' + (1 - \alpha) \bar{y}, j \in \bar{s}_1 \quad (2.2)$$

which represents the weighted mean of the potential predictors $(\bar{y}/\bar{x})\bar{x}'$ and \bar{y} for each $y_j, j \in \bar{s}_1$.

Now, to estimate the population mean \bar{Y} , we follow up the predictive decomposition of Y as given in (1.2) and employing the predictors given in (2.1) and (2.2), the proposed estimator is

$$\bar{y}_{ad} = \alpha \frac{\bar{y}}{\bar{x}} \bar{x}' + (1 - \alpha) \bar{y}. \quad (2.3)$$

Note that, \bar{y}_{ad} reduces to well-known estimators in two-phase sampling via specific values of α , e.g.,

(a) \bar{y}_{rd} (the usual ratio estimator in two-phase sampling given by (1.1))

If $\alpha = 1$;

(b) \bar{y}_{ld} (the usual regression estimator in two-phase sampling) if $\alpha = b\bar{x}/\bar{y}$, where b is the sample regression coefficient.

It is evident that even the predictors \hat{y}_j given in (2.1) and (2.2) in respect of $s_1 \bar{s}_2$ and \bar{s}_1 , respectively, reduce to the known forms, cf. Agrawal and Jain [1]

We refer to Sukhatme et al. ([4], p.213) for a discussion of the other estimators employed in two-phase sampling, namely, the Hartley-Ross, Tin's and Beale's estimators defined by

$$\bar{y}_{HRd} = \bar{r}\bar{x}' + \frac{n(n'-1)}{n'(n-1)} (\bar{y} - \bar{r}\bar{x}) \quad (2.4)$$

$$\bar{y}_{Td} = \bar{y}_{rd} \left[1 - \left(\frac{1}{n} - \frac{1}{n'} \right) \left(\frac{s_x^2}{\bar{x}^2} - \frac{s_{xy}}{\bar{x}\bar{y}} \right) \right] \quad (2.5)$$

$$\text{and } \bar{y}_{Bd} = \bar{y}_{rd} \left[1 + \left(\frac{1}{n} - \frac{1}{n'} \right) \frac{s_{xy}}{\bar{x}\bar{y}} \right] / \left[1 + \left(\frac{1}{n} - \frac{1}{n'} \right) \frac{s_x^2}{\bar{x}^2} \right], \quad (2.6)$$

where $\bar{r} = \frac{1}{n} \sum_{j=1}^n \frac{y_j}{x_j}$, s_x^2 and s_{xy} are, respectively, the sample mean square of x and the sample covariance between x and y . The estimators given in (2.4), (2.5) and (2.6) are obtainable from (2.3) choosing a suitable α in each case.

The results based on predictive approach that is developed here can also apply to one-phase sampling when $n' = N$ in relation to the customary ratio and regression methods of estimation.

III. Performance of the Proposed Estimator vis-à-vis the Competing Estimators in Two-phase Sampling

The mean square error, to the first degree of approximation, of the composite estimator \bar{y}_{ad} , taking α as a pre-assigned weight, is obtained as

$$M(\bar{y}_{ad}) = \left(\frac{1}{n} - \frac{1}{N} \right) S_y^2 + \left(\frac{1}{n} - \frac{1}{n'} \right) (\alpha^2 R^2 S_x^2 - 2\alpha R \rho S_y S_x), \quad (3.1)$$

where ρ is the correlation coefficient between x and y and $R = \bar{Y}/\bar{X}$, the other notations having the same meaning as given in section 1.

The mean square errors, to the first degree of approximation, of \bar{y}_{rd} and \bar{y}_{HRd} given in (1.1) and (2.3), respectively, are known to be

$$M(\bar{y}_{rd}) = \left(\frac{1}{n} - \frac{1}{N} \right) S_y^2 + \left(\frac{1}{n} - \frac{1}{n'} \right) (R^2 S_x^2 - 2R \rho S_y S_x) \quad (3.2)$$

$$\text{and } M(\bar{y}_{HRd}) = \left(\frac{1}{n} - \frac{1}{N} \right) S_y^2 + \left(\frac{1}{n} - \frac{1}{n'} \right) (\bar{R}^2 S_x^2 - 2\bar{R} \rho S_y S_x), \quad (3.3)$$

where $\bar{R} = \frac{1}{N} \sum_{j=1}^N \frac{y_j}{x_j}$, see Sukhatme et al. ([4], pp.212-213). Using (3.1) and (3.2), a condition for better performance of \bar{y}_{ad} relative to \bar{y}_{rd} , namely

$$(\alpha^2 - 1) R S_x - 2(\alpha - 1) \rho S_y \leq 0$$

leads to

$$\rho \geq \left(\frac{1+\alpha}{2} \right) \frac{C_x}{C_y} \text{ if } \alpha \geq 1;$$

otherwise

$$\rho \leq \left(\frac{1+\alpha}{2} \right) \frac{C_x}{C_y} \text{ if } \alpha \leq 1;$$

which, in turn, yield the following equivalent conditions on the range of α :

$$1 \leq \alpha \leq 2\Delta - 1 \text{ if } \Delta \geq 1 \quad (3.4) \text{ otherwise, } 2\Delta - 1 \leq \alpha \leq 1 \text{ if } \Delta \leq 1, \quad (3.5)$$

for which \bar{y}_{ad} is to be preferred to \bar{y}_{rd} where $\Delta = \rho C_y / C_x$ and C_y and C_x are the coefficients of variation of y and x , respectively. It is thus clear from (3.4) and (3.5) that a suitable value of α can invariably be chosen with a view to rendering \bar{y}_{ad} more efficient than \bar{y}_{rd} . Since \bar{y}_{rd} is a widely used estimator, it would be worthwhile to note that the condition $\Delta \geq 1$ always points to the y -variability being higher than the x -variability, while the

condition $\Delta \leq 1$ would often point to the reverse case. As a matter of fact, we are faced with the condition $\Delta \geq 1$ in a large variety of practical situations.

In this context, it would be apt to consider two well-known ratio-type estimators in two-phase sampling given in (2.3) and (2.4), namely, Tin's and Beale's estimators \bar{y}_{Td} and \bar{y}_{Bd} which have the same approximate mean square error as that of \bar{y}_{rd} given in (3.2), see Sukhatme et al. ([4], p.213) and hence, \bar{y}_{ad} would fare better than \bar{y}_{Td} and \bar{y}_{Bd} under the same conditions as given in (3.4) and (3.5).

Analogously, employing (3.1) and (3.3), the conditions on α for \bar{y}_{ad} to perform better than \bar{y}_{HRd} can be expressed as

$$\varphi \leq \alpha \leq 2\Delta - \varphi \text{ if } \Delta \geq \varphi \quad (3.6)$$

$$\text{or } 2\Delta - \varphi \leq \alpha \leq \varphi \text{ if } \Delta \leq \varphi, \quad (3.7)$$

where $\varphi = \bar{R}/R$. It may be noted that

$$\varphi \geq 1 \Rightarrow \bar{R} \geq R \Rightarrow \rho_{zx} \leq 0$$

$$\text{and } \varphi \leq 1 \Rightarrow \bar{R} \leq R \Rightarrow \rho_{zx} \geq 0,$$

where ρ_{zx} is the correlation coefficient between $z=y/x$ and x . Thus, a choice, in accordance with (3.6) or (3.7), of a suitable value of α can unexceptionably be made so that \bar{y}_{ad} fares better than \bar{y}_{HRd} .

Now, a comparison of \bar{y}_{ad} with the usual regression estimator \bar{y}_{ld} in two-phase sampling whose mean square error, to the first degree of approximation, is given by

$$M(\bar{y}_{ad}) = \left(\frac{1}{n} - \frac{1}{N}\right) S_y^2 - \left(\frac{1}{n} - \frac{1}{N}\right) \rho^2 S_y^2$$

shows that the former will be as efficient as the latter when $\alpha = \Delta$.

In the context of our foregoing appraisal of the proposed estimator \bar{y}_{ad} , it is quite natural to examine its performance vis-à-vis the usual sample mean \bar{y} having the variance

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

The results obtained in this section are now concisely presented in Table 3.1.

Table 3.1 Choice of estimator for various values of α

Competing Estimators	Estimator to be used	Choice of α
\bar{y}_{ad} vs \bar{y}_{rd} or \bar{y}_{Td} or \bar{y}_{Bd}	\bar{y}_{ad}	$1 \leq \alpha \leq 2\Delta - 1$ if $\Delta \geq 1$ $2\Delta - 1 \leq \alpha \leq 1$ if $\Delta \leq 1$
\bar{y}_{ad} vs \bar{y}_{HRd}	\bar{y}_{ad}	$\varphi \leq \alpha \leq 2\Delta - \varphi$ if $\Delta \geq \varphi$ $2\Delta - \varphi \leq \alpha \leq \varphi$ if $\Delta \leq \varphi$
\bar{y}_{ad} vs \bar{y}_{ld}	\bar{y}_{ad}	$\alpha = \Delta$
\bar{y}_{ad} vs \bar{y}	\bar{y}_{ad}	$\alpha \leq \Delta$

As evidenced from the above table, a common single value of α that renders \bar{y}_{ad} the best among the competing estimators considered by us is $\Delta (= \rho C_y / C_x)$ which, in fact, yields the minimum value of the mean square error of \bar{y}_{ad} given in (3.1).

As regards the choice of α equal to Δ , it can be said that the population coefficients of variation C_y and C_x and the correlation coefficient ρ may often be more or less known on the basis of past data, experience, a pilot survey or otherwise and hence some prior information on Δ may not be a problem, see Ray and Sahay[3].

To conclude the foregoing discussion, it can be said that the composite estimator \bar{y}_{ad} , employing a suitable choice of α , can invariably be invoked with a view to scoring over the well-known estimators in two-phase sampling.

IV. Performance-Sensitivity due to Lack of Optimality of α

We now appraise performance-sensitivity of \bar{y}_{ad} when optimum α , viz., Δ is not available, meaning thereby that we examine the performance of the estimator \bar{y}_{ad} if the optimum α (i.e., Δ) is not employed and instead we use a weight α , which embodies a certain error in Δ , defined as

$$\alpha = (1 + \delta)\Delta,$$

where δ symbolises proportional deviation in Δ . As a result of use of α in stead of Δ , there will be proportional increase in mean square error measured by

$$P_I = \frac{M(\bar{y}_{ad}) - M(\bar{y}_{ad})_{\alpha=\Delta}}{M(\bar{y}_{ad})_{\alpha=\Delta}},$$

which, for large N , can be worked out as

$$P_I = \left(\frac{1}{n} - \frac{1}{N}\right) \delta^2 \rho^2 / \left(\frac{1-\rho^2}{n} + \frac{\rho^2}{N}\right)$$

and the same can then yield

$$P_I \leq \delta^2 \text{if } \rho^2 < \frac{n'}{2(n'-n)}, \tag{4.1}$$

which will always hold if $n' \leq 2n$. From (4.1), it is clear that, if $n' \leq 2n$, the proportional increase in mean square error (P_I) resulting from lack of optimality of α would be less than the square of proportional deviation δ in optimum α . In other words, if δ is of the order of 10% or 20%, then P_I will not exceed 1% or 4% as the case may be.

However, we can obtain P_I as

$$P_I = \delta^2 \left\{ \frac{V(\bar{y}) - M(\bar{y}_{ad})_{\alpha=\Delta}}{M(\bar{y}_{ad})_{\alpha=\Delta}} \right\},$$

from which it can be interpreted that P_I is δ^2 times the gain in efficiency of $(\bar{y}_{ad})_{\alpha=\Delta}$ relative to \bar{y} .

From the above results, we can conclude that, unless δ is quite large, the inflation in variance of \bar{y}_{ad} resulting from the use of non-optimum α will not be significant. Note that P_I is symmetric with respect to deviations from Δ .

V. Numerical Illustration

We now illustrate the performance of the composite estimator \bar{y}_{ad} vis-à-vis some well-known estimators in two-phase sampling.

For a certain population, it is a priori known that $\Delta = 0.60$. On the basis of a sample survey, the following quantities are obtained:

$$N=117, n'=40, n=17, \hat{R} = \bar{y}/\bar{x} = 0.99, \bar{r} = \frac{1}{n} \sum_{j=1}^n y_j/x_j = 1.00, s_y^2=287.85, s_x^2=458.56 \text{ and } \hat{\rho} = 0.72.$$

For the above example, the estimated relative efficiency of each of the estimators \bar{y}_{rd} (or \bar{y}_{Td} or \bar{y}_{Bd}), \bar{y}_{HRd} and \bar{y}_{ad} with respect to \bar{y} is presented in Table 5.1 given below.

Table 5.1 Estimated relative efficiency of the competing estimators w.r.t. \bar{y}

Estimator	Estimated Relative Efficiency w.r.t. \bar{y}
\bar{y}	1.00
\bar{y}_{rd} or \bar{y}_{Td} or \bar{y}_{Bd}	1.19
\bar{y}_{HRd}	1.18
\bar{y}_{ad} (with $\alpha = \Delta = 0.60$)	1.53

The above table demonstrates that, in the context of two-phase sampling, appreciable gain in efficiency can be achieved through the use of \bar{y}_{ad} .

In the light of our findings of section 4, we examine the impact of variation in $\Delta (=0.60)$ on the relative efficiency of \bar{y}_{ad} . For this purpose, we have prepared the following table:

Table 5.2 Impact of variation in Δ on the relative efficiency of \bar{y}_{ad}

$\alpha = \hat{\Delta}$ (guessed Δ)	Estimated Loss in Efficiency of $(\bar{y}_{ad})_{\alpha=\Delta}$
0.45	0.0331
0.55	0.0037
0.65	0.0037
0.75	0.0031

Table 5.2 makes it abundantly clear that even if Δ is subject to the error to the extent of 25%, the superiority of $(\bar{y}_{ad})_{\alpha=\Delta}$ remains considerably intact in the sense that the estimated loss in efficiency is around 3% or less.

VI. Conclusion

Besides being predictive in character, the newly proposed estimator in two-phase sampling excels its competing estimators from the standpoint of efficiency if the weighting factor is optimally determined. In case there is a problem in the determination of optimum weighting factor, one can go ahead with a guessed value since the variation between the true value and the guessed value results in a negligible loss in efficiency.

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References

- [1]. M.C. Agrawal and N. Jain. Predictive estimation in double sampling procedures. American Statistician. 42. 1988. 184-186.
- [2]. M.C. Agrawal and N. Jain. A new predictive product estimator. Biometrika. 76. 1989. 822-823.
- [3]. S.K. Ray and A. Sahai. Efficient families of ratio and ratio-type estimators. Biometrika. 67. 1980. 211-215.
- [4]. P. V. Sukhatme, B. V. Sukhatme, S. Sukhatme and C. Asok. Sampling theory of surveys with applications. (ISAS, New Delhi, India and Iowa State University Press, Iowa, U.S.A. 1980)