Two-phase Ratio-type Estimator of a Finite Population Mean

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Abstract-- This paper deals with the estimation of a finite population mean under two-phase sampling in presence of two auxiliary variables. A ratio-type estimator is proposed and its approximate properties are presented. An empirical study is carried out using three natural populations to compare the performance of the proposed estimator with other estimators discussed in this paper.

Keywords-- Auxiliary variables, mean square error (MSE), ratio and regression estimators, simulation, two-phase sampling

I. INTRODUCTION

Sampling has been the most significant phase of conducting a survey. The problem of estimation of the population mean or total of the survey variable, incorporating auxiliary information on one or two variables at estimation stage, in single-phase and two-phase sampling has been considered by many authors. Neyman [1] introduced the concept of two-phase sampling. In two-phase sampling a large sample is selected at first phase to estimate the auxiliary variable and at second stage the variable of interest is estimated. Two-phase sampling is more efficient and more flexible method for estimation. Numbers of estimators are developed in literature where auxiliary information has increased the efficiency of the estimators. Several ratio and regression type estimators are also introduced to estimate the parametric values of the variable of interest. In the cases where the study variable and the auxiliary variable are highly correlated ratio-type estimator have proven to be the most efficient one. Cochran [2] developed ratio and regression estimators under two-phase sampling to estimate the population mean using one auxiliary variable. For further reading see Khosnevisan [3], Kadilar and Cingi [4], Gupta and Shabbir [5], and references cited in these papers. Many often, extra auxiliary variable \( z \) closely related to \( x \) but compared to \( x \) remotely relate to \( y \) is available. For example, \( x \) is current value of a characteristic and \( z \) is some previous value of the same characteristic in such case two auxiliary variables are used for estimation. Chand [6] extended the concept of Cochran [2] and developed a chain ratio type estimator under two-phase sampling. Kiregyera [7,8] suggested various estimators using two auxiliary variables under two-phase sampling. Nazir et al. [9] developed an estimator for the population mean under stratified sampling using two auxiliary variables. Motivated from the above work, in such situations, we wish to estimate the population mean under two-phase sampling using simple random sampling at both the phases. The research article is aligned as follows: Section I as introduction, Section II as Related work, Section III contains proposed estimator and methodology, Section IV as empirical comparison and Section V as conclusion.

II. RELATED WORK

Consider a finite population of \( N \) identifiable units with the study variable \( y \) and auxiliary variables \( x \) and \( z \). Let \((\overline{y}, \overline{x}, \overline{z})\), \((\gamma_x, \gamma_z)\) and \((\rho_{yx}, \rho_{yz}, \rho_{xz})\) denote the population means, coefficients of variation and correlation coefficients respectively. We consider the problem of estimation of the population mean \( \overline{y} \), incorporating partial information on \( x \) and full information on \( z \) at estimation stage, under two-phase sampling in which a preliminary random sample \( s' \) of size \( n' \) is drawn from the population using simple random sampling without replacement (srswor) and a subsample \( s \) of size \( n \) is drawn using the same sampling design.
The ratio and regression estimators (Cochran, 1977) of \( \bar{Y} \) under two-phase sampling are given by

\[
\hat{Y}_{rd} = \frac{\bar{Y}}{\bar{x}} \tag{1}
\]

and

\[
\hat{Y}_{regd} = \bar{Y} + b_{yx}(\bar{x}' - \bar{x}) \tag{2}
\]

where \( \bar{x}' \) = the mean of \( x \) for preliminary sample, \( \bar{Y}(\bar{x}) \) = the mean of \( y(x) \) variable for sub-sample, and \( b_{yx} \) = subsample regression coefficient between \( y \) and \( x \).

Chand [6] suggested a chain ratio estimator

\[
\hat{Y}_{c} = \frac{\bar{Y}}{\bar{x'}} \cdot \bar{z} \tag{3}
\]

Kiregyera [7,8], noting that this estimator is not preferable when the regression of \( x \) on \( z \) is linear but does not pass through the origin, suggested the ratio-to-regression, ratio-in-regression and regression-in-regression estimators

\[
\hat{Y}_{k1} = \frac{\bar{Y}}{\bar{x}} \left[ \bar{x}' + b_{z\bar{x}}(\bar{z} - \bar{z}') \right] \tag{4}
\]

\[
\hat{Y}_{k2} = \bar{Y} + b_{y\bar{x}}(\bar{z}\bar{Z}/\bar{x} - \bar{x}) \tag{5}
\]

\[
\hat{Y}_{k3} = \bar{Y} + b_{y\bar{x}}(\bar{x}' + b_{z\bar{x}}(\bar{z} - \bar{z}') - \bar{x}) \tag{6}
\]

The approximate MSEs of the estimators given in (1) to (6) are available in Ahmed et al. [10].

III. PROPOSED ESTIMATOR AND METHODOLOGY

The proposed estimator is

\[
\hat{Y}_{prop} = \frac{\bar{Y}}{\bar{x}} \bar{x}' \left[ \frac{\bar{z}}{\bar{Z} - \bar{y}_{xz} \bar{c}_{y} \bar{c}_{z}(\bar{z} - \bar{z}')/\bar{Z}} \right] \tag{7}
\]

where \( \bar{z}' \) = preliminary sample mean of \( z \), \( c_{y} \) = subsample coefficient of variation of \( y \) and \( r_{yz} \) = subsample correlation coefficient between \( y \) and \( z \).

Using the Taylor linearization technique and Equations (10.12) and (10.13) given in Stuart and Ord [11] we obtain the approximate bias and MSE of the proposed estimator as follows. Expanding \( \hat{Y}_{prop} \) around \( \bar{Y} \) using the Taylor series expansion, retaining the terms up to order \( O(n^{-1}) \), we find the variance of \( \hat{Y}_{prop} \) as

\[
V(\hat{Y}_{prop}) = V(\bar{y}) + \left( \frac{\bar{y}}{\bar{x}} \right)^2 V(\bar{x}) + \left( \frac{\bar{y}}{\bar{x}} \right)^2 V(\bar{x}') + \left( -\frac{\bar{y}\bar{p}_{yx}\bar{c}_{y}}{\bar{Z}\bar{c}_{z}} \right)^2 V(\bar{z}) \]

\[
-2 \frac{\bar{y}}{\bar{x}} Cov(\bar{y}, \bar{x}) + 2 \bar{y} \bar{X} Cov(\bar{y}, \bar{x}') - 2 \bar{y} \bar{Z} \bar{p}_{yz} \bar{c}_{y} \bar{c}_{z} Cov(\bar{y}, \bar{z}') \]

\[
-2 \left( \frac{\bar{y}}{\bar{x}} \right)^2 Cov(\bar{x}, \bar{x}') + 2 \frac{\bar{y}^2}{\bar{Z}\bar{X}} \bar{p}_{yx} \bar{c}_{y} \bar{c}_{z} Cov(\bar{x}, \bar{z}') - 2 \frac{\bar{y}^2}{\bar{Z}\bar{X}} \bar{p}_{yx} \bar{c}_{y} \bar{c}_{z} Cov(\bar{x}', \bar{z}') \]
Inserting variances and covariances under two-phase sampling (Singh et al. [12]) we obtain

\[ V(\widehat{Y}_{prop}) = \hat{\gamma}^2 \left[ f_1 (C_y^2 + C_x^2 - 2\rho_{xy}C_yC_x) - f_2 (C_y^2 - \rho_{xy} - \rho_{yx}^2 C_y^2) \right] \]

\[ = \hat{\gamma}^2 \left[ f_1 (C_y^2 + C_x^2 - 2\rho_{xy}C_yC_x) - f_2 (1 - \rho_{yx}^2) C_y^2 \right] \]

where

\[ f_1 = n^{-1} - N^{-1}, \quad f_2 = n^{-1} - N^{-1}, \quad f_3 = f_1 - f_2 \]

Likewise, we can find the bias as

\[ \text{Bias}(\widehat{Y}_{prop}) = \hat{\gamma} \left[ f_3 (C_y^2 - 2\rho_{xy}C_yC_x) + f_2 \left( (\rho_{xy} C_y/C_x)^2 C_y^2 - \rho_{yx} C_y C_y C_x \right) \right] \]

\[ = \hat{\gamma} \left[ f_3 (C_y^2 - 2\rho_{xy}C_yC_x) \right] \]

The bias is negligible if \( n \) is large and relative bias vanishes if \( C_x^2 = C_yC_x \) i.e., the regression lines pass through the origin.

IV. EMPIRICAL COMPARISON

The approximate variance (Ahmed et al. [9]) of each of the estimator given in (1) to (6) and in (7) are computed using each of the real population described below and the performance of an estimator \( \widehat{Y} \) is calculated in terms of percentage relative efficiency (PRE), \( \text{PRE} = (MSE(\widehat{Y}_{rd})/MSE(\widehat{Y})) \times 100 \)

and presented in Table I.

Further, the preceding estimators are compared empirically using a Monte Carlo simulation. For this a preliminary sample of size \( n' \) and a subsample of size \( n \) is selected using two-phase srswor sampling and the values of each estimator are calculated. This procedure is repeated \( M = 5000 \) times.

For each estimator \( \widehat{Y} \) the relative bias in percentage (RB %) and relative efficiency in percentage (RE %) are calculated as

\[ \text{RB}(\widehat{Y}) = 100 \times (\widehat{Y} - \overline{Y})/\overline{Y}, \]

\[ \text{RE}(\widehat{Y}) = \frac{\text{MSE}_{sim}(\widehat{Y}_{rd})}{\text{MSE}_{sim}(\widehat{Y})} \times 100 \]

where

\[ \overline{Y} = \frac{\sum_{j=1}^{M} \widehat{Y}_j}{M} \quad \text{and} \quad \text{MSE}_{sim}(\widehat{Y}) = \frac{\sum_{j=1}^{M} (\widehat{Y}_j - \overline{Y})^2}{(M - 1)} \]

The RB% and RE% are compiled in Table II.

Data set I : Cochran [2] (The observations are replicated 7 times)
\( y \): number of paralytic polio cases in the placebo group
\( x \): number of placebo children
\( z \): number of non-inculcated
\( N = 238, \ n' = 80, \ n = 30, \ \overline{Y} = 2.59, \ \overline{X} = 4.92, \ \overline{Z} = 8.37, \)
\( \rho_{yx} = 0.7328, \quad \rho_{yz} = 0.7290, \quad \rho_{xz} = 0.9014, \quad C_y = 0.0546, \)
\( C_x = 1.0103, \quad C_z = 1.015, \quad \beta_1(x) = 2.38, \quad \beta_2(z) = 8.93 \)
Data set II: Jobson [13] (The observations are replicated 2 times)

\( y \): Highway Rate
\( x \): Weight
\( z \): Engine size

\[ N = 194, \ n' = 80, \ n = 30, \ \overline{Y} = 68.37, \ \overline{X} = 2973.71, \ \overline{Z} = 27.60, \]
\[ \rho_{yx} = 0.7790, \ \rho_{yz} = 0.7464, \ \rho_{xz} = 0.8862 \]
\[ C_y = 0.1869, \ C_x = 0.1761, \ C_z = 0.4395, \ \beta_1(z) = 0.9441, \ \beta_2(z) = 2.5386 \]

Data set III: Murthy [14]

\( y \): Number of cultivators in 1961 census
\( x \): Number of households in 1961 census
\( z \): area in sq. miles in 1951 census

\[ N = 128, n' = 50, n = 20, \overline{Y} = 853.5, \overline{X} = 727.57, \overline{Z} = 5.592 \]
\[ \rho_{yx} = 0.7733, \ \rho_{yz} = 0.6612, \ \rho_{xz} = 0.5591 \]
\[ C_y = 0.6730, \ C_x = 0.5973, \ C_z = 0.6195, \ \beta_1(z) = 0.8840, \ \beta_2(z) = 3.3371 \]

Table I. PRE of different estimators with respect to \( \hat{\bar{Y}}_{rd} \)

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Data I</th>
<th>Data II</th>
<th>Data III</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{\bar{Y}}_{rd} )</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{regd} )</td>
<td>101.09</td>
<td>103.55</td>
<td>101.62</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_C )</td>
<td>96.17</td>
<td>36.75</td>
<td>89.44</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{k1} )</td>
<td>132.10</td>
<td>133.49</td>
<td>125.43</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{k2} )</td>
<td>114.67</td>
<td>69.07</td>
<td>157.10</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{k3} )</td>
<td>133.65</td>
<td>140.31</td>
<td>125.98</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{prop} )</td>
<td>304.71</td>
<td>293.09</td>
<td>440.53</td>
</tr>
</tbody>
</table>

Table II. RB (%) and RE (%)

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Relative Bias (%)</th>
<th>Relative Efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Population</td>
<td>Population</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{rd} )</td>
<td>0.28</td>
<td>-0.03</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{regd} )</td>
<td>0.27</td>
<td>-0.03</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_C )</td>
<td>0.46</td>
<td>0.08</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{k1} )</td>
<td>0.76</td>
<td>-0.15</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{k2} )</td>
<td>0.45</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{k3} )</td>
<td>0.52</td>
<td>-0.02</td>
</tr>
<tr>
<td>( \hat{\bar{Y}}_{prop} )</td>
<td>0.37</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

From Tables I and II it is seen that the proposed estimator has reasonable absolute bias and has performed very well for all the populations considered under study.
V. CONCLUSION

Under the assumptions that extra auxiliary variable \( z \) closely related to \( x \) but compared to \( x \) remotely relate to \( y \) is available and the relation between the study variable and the main auxiliary variable is straight line passing through the origin a ratio-type estimator is proposed. In such circumstances, our estimator may be more suitable than the estimators included in the paper. This is supported by the empirical study presented above. The estimators discussed in this paper can be further extended in many ways, e.g., using regression method of estimation, estimation of ratio of two study variables, incorporating non-response (Kumar and Kumar [15]) etc.

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REFERENCES


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