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A Generalised Class of Unbiased Seperate Regression Type Estimator under Stratified Random Sampling

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Abstract: *In this paper a generalized class of regression type estimators using the auxiliary information on population mean and population variance is proposed under stratified random sampling. In order to improve the performance of the proposed class of estimator, the Jack-knifed versions are also proposed. A comparative study of the proposed estimator is made with that of separate ratio estimator, separate product estimator, separate linear regression estimator and the usual stratified sample mean. It is shown that the estimators through proposed allocation always give more efficient estimators in the sense of having smaller mean square error than those obtained through Neyman Allocation.*
Keywords*: Auxiliary information, ratio type Estimator, Bias, Mean Square Error.*

I. Introduction of the Proposed Estimator

Let a population of size 'N' be stratified in to 'L' non-overlapping strata, the h^{th} stratum size being N_h (h=1,2,……,L) and $\sum_{h=1}^{L} N_h = N$. Suppose 'y' be charectarstic under study and 'x' be the auxiliary variable. We denote by

y_{hj}: The observation on the j^{th} unit of the population for the charectarstic 'y' under study $(j = 1, 2, ..., N_h)$ in the h^{th} stratum (h =1,2,…..,L)

x_{hj}: The observation on the j^{th} unit of the population for the auxiliary charectarstic 'x' under study $(j = 1, 2, ..., N_h)$ in the h^{th} stratum (h = 1,2,….,L).

$$\bar{Y}_h = \frac{1}{N_h}\sum_{j=1}^{N_h} y_{hj}, \bar{X}_h = \frac{1}{N_h}\sum_{j=1}^{N_h} x_{hj},$$

$$S_{yh}^2 = \frac{1}{(N_h - 1)}\sum_{h=1}^{N_h}(y_{hj} - \bar{Y}_h)^2, S_{xh}^2 = \frac{1}{(N_h - 1)}\sum_{j=1}^{N_h}(x_{hj} - \bar{X}_h)^2$$

$$\sigma_{xh}^2 = \frac{1}{N_h}\sum_{j=1}^{N_h}(x_{hj} - \bar{X}_h)^2, \sigma_{yh}^2 = \frac{1}{N_h}\sum_{j=1}^{N_h}(y_{hj} - \bar{Y}_h)^2$$

$$S_{xyh} = \frac{1}{(N_h - 1)}\sum_{j=1}^{N_h}(x_{hj} - \bar{X}_h)\ (y_{hj} - \bar{Y}_h) = \rho_h S_{xh} S_{hj}$$

where ρ_h is the population correlation coefficient between 'x' and 'y' for the h^{th} stratum $(j = 1, 2, ..., N_h)$.

$$R_h = \frac{\bar{Y}_h}{\bar{X}_h}, C_{yh}^2 = \frac{S_{yh}^2}{\bar{Y}_h^2} = \frac{\mu_{02h}}{\bar{Y}_h^2}, C_{xh}^2 = \frac{S_{xh}^2}{\bar{X}_h^2} = \frac{\mu_{20h}}{\bar{X}_h^2}$$

$\mu_{pqh} = \frac{1}{N_h}\sum_{j=1}^{L}(x_{hj} - \bar{X}_h)^p (y_{hj} - \bar{Y}_h)^q$: the $(p,q)^{th}$ population product moment about mean between 'x' and 'y' for the h^{th} stratum $(h = 1, 2, ..., L)$.

$$\beta_{1h} = \frac{\mu_{30h}^2}{\mu_{20h}^2}, \beta_{2h} = \frac{\mu_{40h}^2}{\mu_{20h}^2},$$

$\beta_h = \frac{S_{xyh}}{S_{xh}^2} = \rho_h \frac{S_{yh}}{S_{xh}}$ be the population regression coefficient of y on x for the h^{th} stratum $(h = 1, 2, ..., L)$.

Let a simple random sample of size n_h be selected from the h^{th} stratum without replacement, without any loss of generality, we assume that first n_h units have been selected in the h^{th} stratum from N_h units by SRSWOR. Moreover we assume that N_h is so large that $1-f_h \approx 1$.

We define

$$\bar{y}_h = \frac{1}{n_h}\sum_{j=1}^{n_h} y_{hj}, \bar{x}_h = \frac{1}{n_h}\sum_{j=1}^{n_h} x_{hj}, s_{xh}^2 = \frac{1}{n_h-1}\sum_{j=1}^{n_h}(x_{hj}-\bar{x}_h), s_{yh}^2 = \frac{1}{n_h-1}\sum_{j=1}^{n_h}(y_{hj}-\bar{y}_h)$$

$$\hat{\sigma}_{xh}^2 = \frac{1}{n_h}\sum_{j=1}^{n_h}(x_{hj}-\bar{x}_h)^2, \hat{\sigma}_{yh}^2 = \frac{1}{n_h}\sum_{j=1}^{n_h}(y_{hj}-\bar{y}_h)^2, s_{xyh} = \frac{1}{n_h-1}\sum_{j=1}^{n_h}(x_{hj}-\bar{x}_h)(y_{hj}-\bar{y}_h), b_h = \frac{s_{xyh}}{s_{xh}^2}$$

Assuming that $\bar{X}_h$ is known $\forall h = 1,2,......,L$ .The proposed generalized estimator $\hat{\bar{Y}}_{gS}$ for estimating the population mean $\bar{Y}$ of the study variable is given by

$$\hat{\bar{Y}}_{gS} = \sum_{j=1}^{L} W_h \left\{ \bar{y}_h g(\bar{w}_h) + b_h(\bar{X}_h - \bar{x}_h) \right\} \qquad (1.1)$$

where $\bar{w}_h = \frac{\hat{\sigma}_{xh}^2}{\sigma_{xh}^2}$ and $g(\bar{w}_h)$ is such that $g(\bar{w}_h)=1$ at $w_h = 1$, is a function of w_h satisfying the following conditions.

1. whatever be the sample chosen w_h assumes values in the bounded closed interval 'I' of the real line containing the point unity
2. In the interval 'I' the function $g(\bar{w}_h)$ is continuous and bounded.
3. The first, second and third order derivatives of $g(\bar{w}_h)$ exist and are continuous.

Strata means $\bar{X}_h$ and strata variances σ_{xh}^2 of the auxiliary variables x are assumed to be known. It should be noted that for $g(\bar{w}_h)=1$ the proposed generalized estimator reduces to the separate linear regression estimator given by

$$\bar{y}_{LRS} = \sum_{j=1}^{L} W_h \left\{ \bar{y}_h + b_h(\bar{X}_h - \bar{x}_h) \right\} \qquad (1.2)$$

II. Bias And Mean Square Error of the Proposed Estimator $\hat{\bar{Y}}_{gS}$

Expanding $g(\bar{w}_h)$ about the point $w_h = 1$ in the third order taylor's series from (1.1)

$$\hat{\bar{Y}}_{gs} = \sum_{h=1}^{L} W_h \left[\bar{y}_h \left\{ g(1) + (w_h-1)g'(1) + \frac{(w_h-1)^2}{2!}g''(1) + \frac{(w_h-1)^3}{3!}g'''(w_h^*) \right\} + b_h(\bar{X}_h - \bar{x}_h) \right] \qquad (2.1)$$

where $w_h^* = 1+\theta(w_h-1); 0<\theta<1$ and θ may depend on w_h; $g'(1), g''(1), g'''(w_h^*)$ denotes first second and third order partial derivatives of $g(\bar{w}_h)$ at points w=1,1, w^* respectively.

Let

$$\bar{y}_h - \bar{Y} = e_{0h}, \bar{x}_h - \bar{X} = e_{1h}, s_{xyh} - S_{xyh} = e_{2h}, s_{xh}^2 - S_{xh}^2 = e_{3h}, \hat{\sigma}_{xh}^2 - \sigma_{xh}^2 = e_{4h}$$

$$E(e_{0h}) = E(e_{1h}) = E(e_{2h}) = E(e_{3h}) = E(e_{4h}) = 0; \forall h = 1,2,.....L$$

Now, from (5.2.1), we have

$$\hat{\bar{Y}}_{gS} = \sum_{j=1}^{L} W_h \left\{ \begin{array}{l} \bar{Y}_h + e_{0h} + g'(1)\bar{Y}_h\left(\frac{e_{4h}}{\sigma_{xh}^2} + \frac{e_{0h}e_{4h}}{\bar{Y}_h\sigma_{xh}^2}\right) + \frac{e_{xh}^2}{2\sigma_{xh}^4}g''(1)\bar{Y}_h \\ \beta_h\left(1+\frac{e_{2h}}{S_{xyh}}\right)\left(1-\frac{e_{3h}}{S_{xh}^2}+......\right)(-e_{1h}) \end{array} \right\}$$

$$\hat{\bar{Y}}_{gS} = \sum_{j=1}^{L} W_h \left\{ \begin{array}{l} (\bar{Y}_h + e_{0h})\left\{ g(1) + \frac{e_{4h}}{\sigma_{xh}^2}g'(1) + \frac{e_{xh}^2}{2\sigma_{xh}^4}g''(1) + \frac{e_{xh}^3}{6\sigma_{xh}^6}g'''(w^*) \right\} \\ +\beta_h\left(1+\frac{e_{2h}}{S_{xyh}}\right)\left(1+\frac{e_{3h}}{S_{xh}^2}\right)^{-1}(-e_{1h}) \end{array} \right\}$$

$$\hat{\bar{Y}}_{gS}=\sum_{j=1}^{L}W_h\left\{\bar{Y}_h+e_{0h}+g'(1)\bar{Y}_h\left(\frac{e_{4h}}{\sigma_{xh}^2}+\frac{e_{0h}e_{4h}}{\bar{Y}_h\sigma_{xh}^2}\right)+\frac{e_{xh}^2}{2\sigma_{xh}^4}g''(1)\bar{Y}_h+\beta_h\left(-e_{1h}-\frac{e_{1h}e_{2h}}{S_{xyh}}+\frac{e_{1h}e_{3h}}{S_{xh}^2}+....\right)\right\}$$

(2.2)

Let the sample size be so large that $|e_i|$, i=0,1,2,3,4 ; $\forall h=1,2,......,L$;becomes so small that terms of e_i s having powers greater than two may be neglected.

$$E(\hat{\bar{Y}}_{gS})=\sum_{j=1}^{L}W_h\left\{\bar{Y}_h+g'(1)\frac{E(e_{0h}e_{4h})}{\sigma_{xh}^2}+\bar{Y}_h\frac{g''(1)E\left(e_{4h}^2\right)}{2\sigma_{xh}^4}\beta_h\left(\frac{E(e_{1h}e_{3h})}{S_{xh}^2}-\frac{E(e_{1h}e_{2h})}{S_{xyh}}\right)\right\}$$

Using the results given in Sukhatme and Sukhatme (1997) and proved in appendix

$$E(e_{1h}e_{3h})=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\mu_{30h},E(e_{1h}e_{2h})=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\mu_{21h}$$

$$E(e_{0h}e_{4h})=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\mu_{21h},E\left(e_{4h}^2\right)=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left(\mu_{40h}-\mu_{20h}^2\right);\forall h=1,2,...,L$$

we have,

$$E(\hat{\bar{Y}}_{gS})=\sum_{h=1}^{L}W_h\left[\bar{Y}_h+\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left\{\frac{g'(1)\mu_{21h}}{\sigma_{xh}^2}+\frac{\bar{Y}_hg'(1)}{2\sigma_{xh}^4}\left(\mu_{40h}-\mu_{20h}^2\right)+\beta_h\left(\frac{\mu_{30h}}{S_{xh}^2}-\frac{\mu_{21h}}{S_{xyh}}\right)\right\}\right] \quad (2.3)$$

showing that $\hat{\bar{Y}}_{gS}$ is a biased estimator of population mean $\bar{Y}$ and its bias is given by

$$B(\hat{\bar{Y}}_{gS})=E(\hat{\bar{Y}}_{gS})-\bar{Y}_h$$

$$B(\hat{\bar{Y}}_{gS})=\sum_{h=1}^{L}W_h\left[\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left\{\frac{g'(1)\mu_{21h}}{\sigma_{xh}^2}+\frac{\bar{Y}_hg'(1)}{2\sigma_{xh}^4}.\left(\mu_{40h}-\mu_{20h}^2\right)+\beta_h\left(\frac{\mu_{30h}}{S_{xh}^2}-\frac{\mu_{21h}}{S_{xyh}}\right)\right\}\right] \quad (2.4)$$

The mean square error of $\hat{\bar{Y}}_{gS}$ is given by

$$MSE(\hat{\bar{Y}}_{\theta S})=E(\hat{\bar{Y}}_{\theta S}-\bar{Y})^2=E\left\{\sum_{j=1}^{L}W_h\left(e_{0h}+g'(1)\bar{Y}_h\frac{e_{4h}}{\sigma_{xh}^2}-\beta_he_{1h}\right)^2\right\}$$

(Using (5.2.2) to the first order of approximation)

$$MSE(\hat{\bar{Y}}_{gS})=\sum_{j=1}^{L}W_h\left\{\begin{aligned}&E\left(e_{0h}^2\right)+E\left(\frac{g'(1)^2\bar{Y}_h^2}{\sigma_{xh}^2}e_{4h}^2\right)+E(\beta_h{}^2e_{1h}^2)+2\frac{\bar{Y}_hg'(1)}{\sigma_{xh}^2}E(e_{0h}e_{4h})\\&-2\beta_hE(e_{0h}e_{1h})-2\frac{g'(1)\bar{Y}_h\beta_h}{\sigma_{xh}^2}E(e_{1h}e_{4h})\end{aligned}\right\}$$

Substituting the following results given in Sukhatme and Sukhatme (1997) and proved in appendix

$$E(e_{0h}^2)=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)S_{yh}^2,E(e_{1h}^2)=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)S_{xh}^2,E(e_{0h}e_{1h})=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)S_{xyh}$$

$$E(e_{4h}^2)=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left(\mu_{40h}-\mu_{20h}^2\right),E(e_{0h}e_{4h})=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\mu_{21h}$$

$$E(e_{1h}e_{4h})=\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\mu_{30h};\forall h=1,2,....,L$$

we have

$$MSE\left(\hat{\bar{Y}}_{gS}\right)=\sum_{j=1}^{L}W_h\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left\{\begin{aligned}&S_{yh}^2+\frac{\{g'(1)\}^2\bar{Y}_h^2}{\sigma_X^4}.\left(\mu_{40h}-\mu_{20h}^2\right)+\beta_h{}^2S_{xh}^2\\&+\frac{2g'(1)\bar{Y}_h}{\sigma_{xh}^2}\mu_{21h}-2\beta_hS_{xyh}-\frac{2g'(1)\bar{Y}_h\beta_h}{\sigma_{xh}^2}\mu_{30h}\end{aligned}\right\} \quad (2.5)$$

(2.5) is minimum when

$$g'(1)\bar{Y}_h = \frac{(\beta_h\mu_{20h} - \mu_{21h})}{(\mu_{40h} - \mu_{20h}^2)}\mu_{20h}; \forall h = 1, 2, ..., L \qquad (2.6)$$

and the minimum mean square error of $\hat{\bar{Y}}_{gS}$ is given by

$$MSE\left(\hat{\bar{Y}}_{gS}\right)_{opt} = \sum_{j=1}^{L} W_h\left(\frac{1}{n_h} - \frac{1}{N_h}\right)\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{(\mu_{40h} - \mu_{20h}^2)}\right\}$$

$$MSE\left(\hat{\bar{Y}}_{gS}\right)_{opt} = \sum_{j=1}^{L} W_h\left(\frac{1}{n_h} - \frac{1}{N_h}\right)\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\} \qquad (2.7)$$

III. Optimum Allocation With The Proposed Class

Consider the cost function $C = C_0 + \sum_{h=1}^{L} c_h n_h$, where C_0 is the fixed cost and c_h be the cost of drawing per unit sample within h^{th} stratum respectively, we have

$$V\left(\hat{\bar{Y}}_{gS}\right)_{\min} = \sum_{j=1}^{L}\frac{W_h^2}{n_h}\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{(\mu_{40h} - \mu_{20h}^2)}\right\} \qquad (3.1)$$

we wish to choose n_h such that $V\left(\hat{\bar{Y}}_{gs}\right)_{\min}$ is further least for the fixed cost. To achieve this objective, we apply the Lagrange's method of multipliers for maxima and minima. Accordingly, we define

$$\phi = V\left(\hat{\bar{Y}}_{gS}\right)_{\min} + \lambda\left(\sum_{h=1}^{L} c_h n_h - C + C_0\right) \qquad (3.2)$$

where λ is a constant, known as Lagrange's multiplier.
Differentiating (5.3.2) with respect to n_h and then equating it to zero, we get

$$-\frac{W_h^2}{n_h^2}\left(\frac{1}{n_h} - \frac{1}{N_h}\right)\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\} + \lambda c_h = 0$$

or $$n_h = \frac{1}{\sqrt{\lambda}}\frac{W_h}{\sqrt{c_h}}\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\}^{\frac{1}{2}}; \forall h = 1, 2, ..., L \qquad (3.3)$$

Summing over all strata we have

$$n = \frac{1}{\sqrt{\lambda}}\sum_{j=1}^{L}\frac{W_h}{\sqrt{c_h}}\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\}^{\frac{1}{2}} \qquad (3.4)$$

Taking ratio of (5.3.3) and (5.3.4) we obtain

$$n_h = n\frac{\frac{1}{\sqrt{\lambda}}\frac{W_h}{\sqrt{c_h}}\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\}^{\frac{1}{2}}}{\frac{1}{\sqrt{\lambda}}\sum_{j=1}^{L}\frac{W_h}{\sqrt{c_h}}\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\}^{\frac{1}{2}}} \forall h = 1, 2, ..., L \qquad (3.5)$$

When cost of drawing per unit sample is same in each stratum, (5.3.5)
reduces to:

$$n_h = n\frac{W_h\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\}^{\frac{1}{2}}}{\sum_{j=1}^{L} W_h\left\{(1-\rho_h{}^2)S_{yh}^2 - \frac{(\beta_h\mu_{30h} - \mu_{21h})^2}{\mu_{20h}^2(\beta_{2h} - 1)}\right\}^{\frac{1}{2}}} \forall h = 1, 2, ..., L \qquad (3.6)$$

Substituting the value from (5.3.6) in (5.3.1) we have

$$V\left(\hat{\hat{Y}}_{gS}\right)_{\min.opt} = \frac{1}{n}\sum_{h=1}^{L}\left[W_h\left\{\left(1-\rho_h^{\,2}\right)S_{yh}^2 - \frac{\left(\beta_h\mu_{30h}-\mu_{21h}\right)^2}{\mu_{20h}^2\left(\beta_{2h}-1\right)}\right\}^{\frac{1}{2}}\right]^2 = V_{opt}(say) \qquad (3.7)$$

IV. Concluding Remarks

The mean square error of the separate linear regression estimator is given by

$$MSE(\bar{y}_{LRS}) = \sum_{h=1}^{L}W_h^2\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left(1-\rho_h^2\right)S_{yh}^2 \qquad (4.1)$$

Also the minimum mean square error of the proposed generalized regression type estimator $\hat{\hat{Y}}_{\theta S}$ is given by

$$MSE\left(\hat{\hat{Y}}_{\theta S}\right)_{\min} = \sum_{h=1}^{L}W_h^2\left(\frac{1}{n_h}-\frac{1}{N_h}\right)\left\{\left(1-\rho_h^{\,2}\right)S_{yh}^2 - \frac{\left(\beta_h\mu_{30h}-\mu_{21h}\right)^2}{\mu_{20h}^2\left(\beta_{2h}-1\right)}\right\} \qquad (4.2)$$

Therefore the proposed generalized class of estimators $\hat{\hat{Y}}_{\theta S}$ may be preferred to the separate linear regression estimator, separate ratio estimator, separate product estimator and the usual stratified sample mean in the sense of smaller mean square error. Further the parameter involved θ_h may be estimated by the corresponding sample value in order to get a class of estimators depending upon estimated optimum value.

The variance of stratified sample mean $\bar{y}_{st}$ under Neyman allocation $n_h = n\dfrac{W_h S_{yh}}{\sum_{h=1}^{L}W_h S_{yh}}$

Is given by $V\left(\bar{y}_{st}\right)_{Ney} = \frac{1}{n}\left(\sum_{h=1}^{L}W_h S_{yh}\right)^2$ (ignoring f.p.c) (4.3)

It is evident that V_{opt} is always smaller than $V\left(\bar{y}_{st}\right)_{Ney}$ except for the case when ρ_h=0 and $\beta_h\mu_{30h} = \mu_{21h}$ simultaneously.

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