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An effective imputation method to minimize the effect of random non-response in estimation of population variance on successive occasions

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Abstract

In this paper, an attempt has been made to reduce the negative effect of random non-response in the estimation of population variance on the current occasion in two-occasion successive sampling. A difference type imputation method has been considered to minimize the nuisance effect of random non-response on both occasions. To build up efficient estimation strategies of population variance on current occasion intelligible use of auxiliary information has been made. Estimators are derived for the current occasion as special cases, when random non-response occurs either on the first or on the second occasion. To describe the effectiveness of the proposed estimators, empirical studies are carried out to compare their performances with the natural sample variance and ratio type estimator under the complete response situations. Results are interpreted through empirical studies, which are followed by suitable recommendations.

Keywords : Auxiliary variable; imputation; random non-response; successive sampling; variance estimation.

Mathematics subject classification: 62D05

1. Introduction

The problem of estimation of population variance arises in many practical situations. For example, a physician needs a full understanding of variations in the degree of human blood pressure, body temperature and pulse rate for adequate prescription. The variance estimation technique using auxiliary variable was first considered by Das & Tripathi (1978). Further this was extended by Srivastava & Jhaji (1980), Isaki (1983), Singh (1983), Upadhyay & Singh (1983), Tripathi *et al*. (1988), Singh & Joarder (1998) and Ahamed *et al*. (2003) among others.

The concept of successive sampling was initiated by Jessen (1942). Further, the work have been extended by Feng & Zou (1997), Singh & Karna (2009), Singh *et al*. (2012a), Singh *et al*. (2015) and Singh & Sharma (2014, 2015) among others. Singh *et al*. (2011), Singh *et al*. (2012 a) and Singh *et al*. (2013 b) attempt the estimation of population variance on current occasion in successive sampling, which has huge impact on many realistic situations. To deal with missing values effectively, Sande (1979) suggested imputation methods that make incomplete data sets structurally complete. Several authors including Lee *et al*. (1994), Heitzan & Basu (1996), Singh (2009) and Diana & Perri (2010) have contributed a lot towards generating efficient estimation procedures of population mean in sample surveys with reduced negative impact of non-response through imputation methods.

Motivated by above arguments and using information on an auxiliary variable, present work describes an efficient estimation strategy of population variance on current occasion in presence of random non-response in two-occasion successive sampling. Estimators on the current occasion are also derived for some special cases such as when missing at random (MAR) non-response occurs on either of occasion.

2. Sample structures and notations

Let $U = (U_1, U_2, \ldots, U_N)$ be the finite population of N units, which has been sampled over two occasions. The character under study is denoted by x(y) on the first (second) occasion, respectively. We assume that the study variable x(y) on the first (second) occasion suffering from non-response situation and the information on a stable auxiliary variable z (having positive correlation with study variables y and x) is available on all the units of the population. A simple random sample S_n (without replacement) of n units is drawn on the first occasion. Let the number of units of the study variable x on which random non-response occurs on the first occasion be denoted by $r_1 \{r_1 = 0, 1, 2, ..., (n - 2)\}$ with the set of non-responding units denoted by S_{r_1} and the set (containing

$(n-r_1)$ units) of responding units denoted by $S_{r_1}^c$. It is assumed that a random sub-sample S_m of m units of study variable, x which is retained (matched) for its use on the second (current) occasion from the responding set $S_{r_1}^c$ of the first occasion such that these matched units will respond on the second (current) occasion as well, for instance, see Satici & Kadilar (2011), Singh *et al*. (2012 b) and Singh *et al*. (2013 b) among others. Again a fresh simple random sample S_u (without replacement) of u units is drawn on the second occasion from the entire population so that the sample size on the second (current) occasion is n (= m + u). Let $r_2\{r_2 = 0, 1, 2, ..., (u-2)\}$ be the number of units on which random non-response found out of sampled u units of study variable y drawn afresh on the current occasion. Accordingly we denote the set of non-responding units by S_{r_2} and the set (containing $(u-r_2)$ units) of responding units, by $S_{r_2}^c$. Then the remaining $(n-r_1)$ and $(u-r_2)$ units can be treated as simple random sample from U. If the units belong to the responding unit set, the values on the study variables are observed. However, if they belong to the non-responding unit set, the values on the study variables are missing at random and therefore, the imputed values are derived for such units, which are based on the responding units of the sample. We assumed that $0 \le r_1 \le (n-2)$ and $0 \le r_2 \le (u-2)$. It is assumed that if p_1 and p_2 denote the probability of non-respondent among $(n-2)$ and $(u-2)$ units, respectively, then $r_i\,(i=1, 2)$ have the following discrete distributions as suggested by Singh & Joarder (1998), Singh *et al*. (2000) and Singh *et al*. (2012c) and many more.

$$P(r_1) = \frac{n-r_1}{nq_1 + 2p_1}\,{}^{n-2}C_{r_1} p_1^{r_1} q_1^{n-r_1-2}, r_1 = 0, 1, 2, \ldots, n-2.$$

and

$$P(r_2) = \frac{u-r_2}{uq_2 + 2p_2}\,{}^{u-2}C_{r_2} p_2^{r_2} q_2^{u-r_2-2}, r_2 = 0, 1, 2, \ldots, u-2.$$

where $q_1 = 1-p_1,\ q_2 = 1-p_2$.

Here ${}^{n-2}C_{r_1}$ and ${}^{u-2}C_{r_2}$ are total number of ways obtaining $r_i\,(i=1, 2)$ non-response out of total possible non-responses $n-2$ and $u-2$, respectively.The probability model, defined in above is free from actual data values; hence, can be considered as a model suitable for MAR situation.

Hence, onwards we use the following notations

$\bar{Y}, \bar{X}$: Population means of the study variables y and x respectively.

$\bar{Z}$: Population mean of the auxiliary variable z.

$\bar{z}_u, \bar{z}_{r_2}, \bar{z}_{ur_2}, \bar{z}_{nr_1}$: Sample means of the auxiliary variable z based on the sample of sizes u, r_2, $u-r_2$ and $n-r_1$ respectively.

$\bar{y}_{ur_2}$: Sample mean of the variable y based on units of the responding set $S_{r_2}^c$.

$\bar{x}_{nr_1}$: Sample mean of the variable x based on units of the responding set $S_{r_1}^c$.

$s_{y_{ur_2}}^2$: Sample variance of the variable y based on units of the responding set $S_{r_2}^c$.

$s_{x_{nr_1}}^2$: Sample variance of the variable x based on units of the responding set $S_{r_1}^c$.

$s_{z_{r_2}}^2, s_{z_{ur_2}}^2, s_{z_{nr_1}}^2$: Sample variances of the variable z based on the sample of sizes r_2, $u-r_2$ and $n-r_1$ respectively.

ρ_{yz}, ρ_{xz} : Population correlation coefficients between the variables as shown in subscripts.

S_x^2, S_y^2, S_z^2 : Population variances of the variables x, y and z respectively.

$s_{y_u}^2, s_{y_m}^2, s_{x_m}^2, s_{x_n}^2, s_{z_u}^2, s_{z_n}^2$: Sample variances of the respective variables based on the sample sizes shown in subscripts.

3. Formulation of the estimator T

For estimation of population variance S_y^2 of the study variable y on the second (current) occasion, two estimators T_u and T_m have been formulated and they are structured to cope with the problems of random non-response on both occasions. The estimator T_u is based on the fresh sample S_u of size u drawn on the current occasion and the estimator T_m is based on the sample S_m of size m common to both the occasions.

Now to define the estimator T_u, we express sample variance $s_{y_u}^2$ in the following way

$$s_{y_u}^2 = \frac{1}{2u(u-1)} \sum_{i \ne j}^{u} (y_i - y_j)^2$$

$$= \frac{1}{2u(u-1)} \left[\sum_{\substack{i,j \in S_{r_2}^c \\ i \ne j}} (y_i - y_j)^2 + 2 \sum_{\substack{i \in S_{r_2}^c \\ j \in S_{r_2}}} (y_i - y_j)^2 + \sum_{\substack{i,j \in S_{r_2} \\ i \ne j}} (y_i - y_j)^2 \right] \quad (1)$$

Since, the first component on the right hand side of Equation (1) is available from the responding set $S_{r_2}^c$, while second and third components are missing at random due to random non-responses on the set S_{r_2}. Therefore in order to estimate $s_{y_u}^2$, we have to substitute the missing values of second and third components with certain fabricated values of the responding set $S_{r_2}^c$. Accordingly, we express $s_{y_u}^2$ as

$$s_{y_u}^2 = \frac{1}{2u(u-1)} \left[2(u-r_2)(u-r_2-1) s_{y_{ur_2}}^2 + 2 \sum_{\substack{i \in S_{r_2}^c \\ j \in S_{r_2}}} (y_i - \hat{y}_j)^2 + \sum_{\substack{i,j \in S_{r_2} \\ i \ne j}} (\hat{y}_i - \hat{y}_j)^2 \right] \quad (2)$$

where $s_{y_{ur_2}}^2 = \dfrac{1}{2(u-r_2)(u-r_2-1)} \displaystyle\sum_{\substack{i,j \in S_{r_2}^c \\ i \ne j}} (y_i - y_j)^2$

i.e. sample variance of the variable y based on units of the responding set $S_{r_2}^c$; $\hat{y}_i$ and $\hat{y}_j$ are estimated values of y_i and y_j; $(i, j) \in S_{r_2}$ respectively.

Since, the information on the auxiliary variable z is readily available on all the units of the population, therefore, inspired with the predictive estimation technique of population variance adopted earlier by Agrawal & Roy (1999) and taking the cognizance of the underlying relationship between y and z, we suggest following difference type imputation technique in order to estimate $\{y_i, y_j;\ (i, j) \in S_{r_2}\}$..

$$\hat{y}_i = \bar{y}_{ur_2} + \beta_{yz}\left(z_i - \bar{z}_{ur_2}\right) \text{ and } \hat{y}_j = \bar{y}_{ur_2} + \beta_{yz}\left(z_j - \bar{z}_{ur_2}\right);\ (i, j) \in S_{r_2} \quad (3)$$

where $\hat{y}_i$ and $\hat{y}_j$ are estimated values of y_i and y_j; $(i, j) \in S_{r_2}$ respectively and β_{yz} is the known population regression coefficient between y and z.

Using the above imputation technique Equation (2) reduces to

$$s_{y_u}^{2*} = \frac{1}{2u(u-1)}\left[u(u-r_2-1)s_{y_{ur_2}}^2 + (u-r_2)r_2\beta_{yz}^2\left(\bar{z}_{r_2} - \bar{z}_u\right)^2 + u\beta_{yz}^2\left(r_2-1\right)s_{z_{r_2}}^2\right] \quad (4)$$

where

$$\bar{z}_{r_2} = \frac{1}{r_2}\sum_{i \in S_{r_2}} z_i \text{ and } s_{z_{r_2}}^2 = \frac{1}{r_2 - 1}\sum_{j \in S_{r_2}}\left(z_j - \bar{z}_{r_2}\right)^2$$

Now, using the relations

$$\bar{z}_u = \frac{r_2\bar{z}_{r_2} + (u-r_2)\bar{z}_{ur_2}}{u} \quad (5)$$

and

$$s_{z_u}^2 = \frac{1}{u-1}\left[(r_2-1)s_{z_{r_2}}^2 + (u-r_2-1)s_{z_{ur_2}}^2 + \frac{(u-r_2)r_2}{u}\left(\bar{z}_{r_2} - \bar{z}_{ur_2}\right)^2\right] \quad (6)$$

in Equation (4), we arrive at

$$s_{y_u}^{2*} = \frac{1}{u-1}\left[(u-r_2-1)s_{y_{ur_2}}^2 + \beta_{yz}^2\left\{(u-1)s_{z_u}^2 - (u-r_2-1)s_{z_{ur_2}}^2\right\}\right] \quad (7)$$

Thus, we define the estimator T_u as

$$T_u = s_{y_u}^{2*} \quad (8)$$

The second estimatoris T_m based on the sample S_m, which utilizes the information on an auxiliary variable z as well as information from the first occasion. Since, there is also random non response on the first occasion, the missing values are required to be replaced by derived imputed values and we use the regression type imputation technique described above.

Thus, to derive the imputed values of the study variable $x_i \in S_{r_1}$, we use imputation technique as

$$\hat{x}_i = \bar{x}_{nr_1} + \beta_{xz}\left(z_i - \bar{z}_{nr_1}\right),\ i \in S_{r_1}. \quad (9)$$

where $\hat{x}_i$ is estimated value of x_i; $i \in S_{r_1}$ and β_{xz} is the known population regression coefficient between x and z.

Similarly, consider the revising expressions for finding $s_{y_u}^{2*}$ on current occasion. We find $s_{x_n}^{2*}$ as well which is given below

$$s_{x_n}^{2*} = \frac{1}{n-1}\left[(n-r_1-1)s_{x_{nr_1}}^2 + \beta_{xz}^2\left\{(n-1)s_{z_n}^2 - (n-r_1-1)s_{z_{nr_1}}^2\right\}\right] \quad (10)$$

where

$$s_{x_{nr_1}}^2 = \frac{1}{2(n-r_1)(n-r_1-1)}\sum_{\substack{i, j \in S_{r_1}^c \\ i \neq j}}\left(x_i - x_j\right)^2$$

i. e. sample variance of the variable x based on units of the responding set $S_{r_1}^c$.

Under this method of imputation, the estimator based on sample size m on the first occasion is given by

$$T_m = \frac{s_{y_m}^2}{s_{x_m}^2} s_{x_n}^{2*} \quad (11)$$

Considering the convex linear combination of the estimators T_u and T_m; the estimator T is defined as :

$$T = \varphi T_u + (1-\varphi)T_m \quad (12)$$

where $\varphi\,(0 \le \varphi \le 1)$ is an unknown constant to be determined by the minimization of the variance of the estimator T.

4. Properties of the proposed estimator T

4.1. Bias of the estimator T

The bias of the estimator T up to the first order of approximations as

$$B(T) = \varphi B(T_u) + (1-\varphi)B(T_m) \quad (13)$$

where

$$B(T_u) = S_y^2\theta_2 \quad (14)$$

$$B(T_m) = S_y^2\begin{bmatrix}\theta_1 + \left\{(\theta_1+1)f - \alpha_1 f^*\right\}\left(C_1^2 - \rho_{01}C_0C_1\right) \\ +\rho_{xz}^2\left(f - \alpha_1 f^*\right)\left(\rho_{02}C_0C_2 - \rho_{12}C_1C_2\right)\end{bmatrix} \quad (15)$$

where $\theta_1 = (1-\alpha_1)(\rho_{xz}^2 - 1)$,

4.2. Mean square error of the estimator T

The mean square error of the estimator T up to the first order approximations as

$$M(T) = \varphi^2 M(T_u) + (1-\varphi)^2 M(T_m) \quad (16)$$

where

$$M\left(T_u\right)=S_y^4\left[\theta_2^2+f_2^*\alpha_2^2\left(C_0^2+\rho_{yz}^4C_2^2-2\rho_{yz}^2\rho_{02}C_0C_2\right)+f_2\rho_{yz}^2\begin{Bmatrix}\rho_{yz}^2C_2^2\left(1-2\alpha_2\right)\\+2\alpha_2\rho_{02}C_0C_2\end{Bmatrix}\right] \tag{17}$$

$$M\left(T_m\right)=S_y^4\begin{bmatrix}\theta_1^2+\left(\theta_1+1\right)^2f_1\ t_1+f\left\{\left(1-2\alpha_1\right)\rho_{xz}^4C_2^2+2\rho_{xz}^2\left(\left(\theta_1+1\right)t_2+\alpha_1\rho_{xz}^2\rho_{12}C_1C_2\right)\right\}\\f^*\left\{\alpha_1^2t_3+2\left(\theta_1+1\right)\alpha_1\left(\rho_{01}C_0C_1-C_1^2-\rho_{xz}^2t_2\right)\right\}\end{bmatrix} \tag{18}$$

where $t_1=\left(C_0^2+C_1^2-2\rho_{01}C_0C_2\right)$, $t_2=\left(\rho_{02}C_0C_2-\rho_{12}C_1C_2\right)$, $t_3=C_1^2+\rho_{xz}^4C_2^2-2\rho_{xz}^2\rho_{12}C_1C_2$.

Since, the estimators are based on two independent samples of sizes u and m respectively, therefore,

$$C\left(T_u,T_m\right)=0. \tag{19}$$

4.3. Minimum mean square error of the estimator T

Since the mean square error (MSE) of the estimator T in Equation (16) is a function of unknown constant φ, that is minimized with respect to φ and subsequently the optimum value of φ is obtained as

$$\varphi_{opt}=\frac{M\left(T_m\right)}{M\left(T_u\right)+M\left(T_m\right)} \tag{20}$$

Now substituting the value of φ_{opt} in Equation (20), we have the minimum mean square error of the estimator T as

$$M\left(T\right)_{min}=\frac{M\left(T_u\right).M\left(T_m\right)}{M\left(T_u\right)+M\left(T_m\right)} \tag{21}$$

where $M\left(T_u\right)$ and $M\left(T_m\right)$ are given in the Equations (17) and (18).

5. Special case of occurrence of random non-r esponse only on the first occasion.

When random non-response occurs only on first occasion, the estimator for population variance S_y^2 on current occasion as

$$T^*=\varphi^*\Delta_u+\left(1-\varphi^*\right)T_m \tag{22}$$

$$\text{where } \Delta_u=s_{y_u}^2 \tag{23}$$

and T_m is already shown in Equation (11). $\varphi^*\left(0\le\varphi^*\le1\right)$ is unknown constant to be determined so as to minimize the mean square error of the estimator T^*.

5.1. Properties of the estimator T^*

Since, Δ_u and T_m are sample variance and ratio type estimators, the Δ_u is unbiased and T_m is biased for population variance S_y^2. Therefore, the resulting estimator T^* defined in Equation (23) is also biased estimator of S_y^2.

5.1.1. Bias of the estimator T^*

The bias of the estimator T^* to the first order of approximations as

$$B\left(T^*\right)=\left(\varphi^*\right)B\left(\Delta_u\right)+\left(1-\varphi^*\right)B\left(T_m\right) \tag{24}$$

where $B\left(T_m\right)$ is shown in Equation (15) and

$$B\left(\Delta_u\right)=0 \tag{25}$$

5.1.2. Mean square error of the estimator T^*

The mean square error of the estimator T^* to the first order of approximations as

$$M\left(T^*\right)=\left(\varphi^*\right)^2M\left(\Delta_u\right)+\left(1-\varphi^*\right)^2M\left(T_m\right) \tag{26}$$

where $M\left(T_m\right)$ is already defined in Equation (18) and

$$V\left(\Delta_u\right)=S_y^4f_2C_0^2 \tag{27}$$

5.1.3. Minimum mean square error of the estimator T^*

Proceeding as the section 4.3, we have the expression of minimum MSE of the estimator T^* as shown below

$$M\left(T^*\right)_{min}=\frac{V\left(\Delta_u\right).M\left(T_m\right)}{V\left(\Delta_u\right)+M\left(T_m\right)} \tag{28}$$

where $V\left(\Delta_u\right)$ and $M\left(T_m\right)$ are given in the Equations (27) and (18) respectively.

6, Special case of occurrence of random non-responses only on the second occasion.

When random non-response occurs only on second (current) occasion, the estimator for population variance S_y^2 on current occasion may be obtained as

$$T^{**}=\varphi^{**}T_u+\left(1-\varphi^{**}\right)\Delta_m \tag{29}$$

$$\text{where } \Delta_m=\frac{s_{y_m}^2}{s_{x_m}^2}s_{x_n}^2 \tag{30}$$

and T_u is already defined in Equation (8). $\varphi^{**}\left(0\le\varphi^{**}\le1\right)$ is unknown constant to be determined so as to minimize the MSE of the estimator T^{**}.

6.1. Properties of the estimator T^{**}.

Since, T_u and Δ_m are estimators of variance S_y^2, they are biased for population variance S_y^2. Therefore, the resulting estimator T^{**} defined in Equation (29) is also biased estimator of S_y^2.

6.1.1. Bias of the estimator T^*

The bias of the estimator T^* to the first order of approximations as

$$B(T^{**}) = (\varphi^{**})B(T_u)+(1-\varphi^{**})B(\Delta_m) \quad (31)$$

where $B(T_u)$ is already mentioned in Equation (14) and

$$B(\Delta_m)= S_y^2(f_1- f)(C_1^2 - \rho_{01}C_0C_1) \quad (32)$$

6.1.2. Mean square error of the estimator T^{**}

The mean Square Error of the estimator T^{**} to the first order of approximations is obtained as

$$M(T^*) = (\varphi^*)^2 M(T_u)+(1-\varphi^*)^2 M(\Delta_m) \quad (33)$$

where $M(T_u)$ is already defined in Equation (17) and

$$M(\Delta_m) = S_y^4\left[f_1C_0^2+(f_1- f)(C_1^2- 2\rho_{01}C_0C_1)\right] \quad (34)$$

6.1.3. Minimum mean square error of the estimator T^{**}

Proceeding as the section 4.1, we have the expression of minimum MSE of the estimator T^{**} as shown below

$$M(T^{**})_{min} = \frac{M(T_u).M(\Delta_m)}{M(T_u)+ M(\Delta_m)} \quad (35)$$

where $M(T_u)$ and $M(\Delta_m)$ are given in the Equations (17) and (34) respectively.

7. Efficiency comparisons

To examine the performances of the proposed estimators T, T^* and T^{**}, the percent relative efficiencies of estimators T, T^* and T^{**} with respect to the estimators τ and τ^* of variance S_y^2 under the complete response situations have been examined through empirical studies. The empirical studies are carried out through different two natural population data sets. The merits of the proposed work are shown for different choices of the sample sizes (m, n), non-response probabilities (p_1, p_2) and correlation coefficients ($\rho_{01}, \rho_{02}, \rho_{12}$). Accordingly, the variance estimators τ and τ^* are considered as

$$\tau = \psi\Delta_u+(1- \psi)\tau_m \quad (36)$$

and

$$\tau^* = \psi^*\Delta_u+(1- \psi^*)\Delta_m \quad (37)$$

where $\Delta_u = s_{y_u}^2$, $\tau_m = s_{y_m}^2$ and $\Delta_m = \frac{s_{y_m}^2}{s_{x_m}^2}s_{x_n}^2$; $\psi(0 \le \psi \le 1)$ and $\psi^*(0 \le \psi^* \le 1)$ are unknown constants to be determined by the minimization of mean square error of the estimators τ and τ^*.

Proceeding as sections 4 and 5, the minimum variance of and MSE of to the first order of approximations are obtained as

$$V(\tau)_{min} = \frac{V(\Delta_u).V(\tau_m)}{V(\Delta_u)+ V(\tau_m)} \quad (38)$$

$$M(\tau^*)_{min} = \frac{V(\Delta_u).M(\Delta_m)}{V(\Delta_u)+ M(\Delta_m)} \quad (39)$$

where $V(\tau_m)= S_y^4 f_1 C_0^2$ and $V(\Delta_u)$, $M(\Delta_m)$ are shown in respective Equations (27) and (34).

The expressions of percent relative efficiencies E_1, E_2 of estimator T, E_1^*, E_2^* of estimator T^* and E_1^{**}, E_2^{**} of estimator T^{**} with respect to τ and τ^* under their respective optimality conditions are given by

$$E_1 = \left[\frac{V(\tau)_{min}}{M(T)_{min}}\right]\times 100,\quad E_2 = \left[\frac{M(\tau^*)_{min}}{M(T)_{min}}\right]\times 100,\quad E_1^* = \left[\frac{V(\tau)_{min}}{M(T^*)_{min}}\right]\times 100,$$

$$E_2^* = \left[\frac{M(\tau^*)_{min}}{M(T^*)_{min}}\right]\times 100,\ E_1^{**} = \left[\frac{V(\tau)_{min}}{M(T^*)_{min}}\right]\times 100 \text{ and } E_2^{**} = \left[\frac{M(\tau^*)_{min}}{M(T^*)_{min}}\right]\times 100$$

8. Conclusions

From the preceding analysis, it is clear that the proposed estimators T, T^* and T^{**} contribute significantly to handle the different realistic situations of random non-response, while estimating population variance on current occasion in two-occasion successive sampling, when percent relative efficiencies of the proposed estimators greater than 100. It is discernible that the proposed estimators are more efficient than the sample variance estimator τ and τ^* under the complete response situations. Thus, it is established that the use imputation technique in the structures of the proposed estimators are highly rewarding in terms increased precession of estimates as well as reducing the cost of survey and negative impact of non-responses. Hence, the proposition of the suggested estimators in the present study is justified as they unify several highly desirable results. Therefore, proposed estimators may be recommended for their practical applications to the survey statisticians.

References

Agrawal, M. C. & Roy, D. C (1999). Efficient estimators of population variance with regression-type and ratio-type predictor- inputs. Metron, LVII (3):169-178.

Ahmed, M. S. Abu - Dayyeh, W. & Hurairah, A. A. O. (2003). Some estimators for population variance under two phase sampling. Statistics in Transition, **6**(1):143-150.

Das, A. K. & Tripathi, T. P. (1978). Use of auxiliary information in estimating the finite population variance. Sankhya, **34**:1-9.

Diana, G. & Perri, P. F. (2010). Improved estimators of the population mean for missing data. Communications in Statistics-Theory and Methods, **39**:3245-3251.

Feng, S. & Zou, G. (1997). Sample rotation method with auxiliary variable. Communications in Statistics-Theory and Methods, **26**, 6:1497-1509.

Heitzan, D. F. & Basu, S. (1996). Distinguish 'missing at random' and 'missing completely at random. Amer. Statistician **50**:207-217.

Isaki, C. T. (1983). Variance estimation using auxiliary information. Journal of the American Statistical Association, **78**:117-123.

Jessen, R. J. (1942). Statistical investigation of a sample survey for obtaining farm facts, Iowa Agricultural Experiment Station Research Bulletin No. 304, Ames, Iowa, U. S. A., 1-104.

Lee, H., Rancourt, E. & Sarndall, C. E (1994). Experiments with variance estimation from survey data with imputed values. Journal of Official Statistics, **10**(3):231-243.

Sande, I. G. (1979). A Personal view of hot-deck imputation procedures. Survey Methodology, **5**:238-247.

Satici E. & Kadilar C. (2011). Ratio estimator for the population mean at the current occasion in the presence of non-response in successive sampling. Hacettepe Journal of Mathematics and Statistics, **40**(1):115-124.

Singh R. K. (1983). Estimation of population variance using ratio and product methods of estimation, Biometika. Journal, **25**(2):193-200.

Singh, G. N & Sharma, A. K. (2014). An Alternative rotation patterns in two occasion successive sampling. . International Journal of Mathematics and Statistics, **5**(3):9-22.

Singh, G. N & Sharma, A. K (2015). Search of some effective rotation patterns in two-occasion successive sampling. Journal of statistics application and probability, **4**(1):127-138.

Singh, G. N. & Karna, J.P. (2009) Estimation of peopulation mean on the current in two- occasion successive sampling, Metron, **67**(1):87-103.

Singh, G. N., Majhi D., Prasad S. & Homa F. (2013b). Assessment of non-response under ratio method of imputation in two-occasion successive sampling. Journal of Statistical Theory and Applications, **12**(4):403-418.

Singh, G. N., Majhi, D., Maurya, S. & Sharma, A. K. (2015). Some effective rotation patterns in estimation of population mean in two-occasion successive sampling. Communications in Statistics-Theory & Methods, **44**(12):2571-2585.

Singh, G. N., Prasad, S. & Majhi, D. (2012a). Best linear unbiased estimators of population variance in Successive Sampling. Model Assisted Statistics and Applications, (7):169- 178.

Singh, G. N., Priyanka, K., Prasad, S., Singh, S. & Kim, J. M. (2013a). A class of estimators for population variance in two occasion rotation patterns. Communications for Statistical Applications and Methods, **20**(4):247–257.

Singh, G. N., Singh, V. K., Priyanka, K., Prasad, S. & Karna, J. P. (2012b). Rotation patterns under imputation of missing data over two-occasion. Communications in Statistics - Theory and Methods, **41**(4):619-637.

Singh, H. P., Tailor, R., Kim, J. M. & Singh, S. (2012c). Families of estimators of finite population variance using a random non-response in survey sampling. The Korean Journal of Applied Statistics, **25**(4):681-695.

Singh, H. P., Tailor, R., Singh, S. & Kim, J. M. (2011). Estimation of population variance in successive sampling. Quality Quantity. **45**:477-494.

Singh, S. (2009). A new method of imputation in survey sampling. Statistics, **43**(5):499-511.

Singh, S. & Joarder, A. H. (1998). Estimation of finite population variance using random non-response in survey sampling. Metrika, **47**:241-249.

Singh, S., Joarder, A. H. & Tracy, D. S. (2000). Regression type estimators of random non-response in survey sampling. Statistica. LX, **1**:39-44.

Srivstava, S. K. & Jhaji, H. S. (1980). A class of estimators using auxiliary information for estimating finite population variance. Sankhya, C, **42**:87-96.

Tripathi, T. P., Singh, H. P. & Upadhyaya, L. N. (1988). A generalized method of estimation in double sampling. Journal of the Indian. Statistical. Association, **26**:91-101.

Upadhyaya, L. N. & Singh, H. P. (1983). Use of auxiliary information in the estimation of population variance. Mathematical Forum, **6**(2):33-36.

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طريقة حساب فعالة لتصغير
تأثير عم الرد عند تقدير تباين المجتمع في مواضع متتابعة

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خــلاصــة

نحاول في هذا البحث تقليل التأثير السلبي لعدم الرد العشوائي عند تقدير تباين المجتمع في الموضع الحالي عند أخذ العينة في موضعين متتابعين. نستخدم طريقة للحساب تعتمد على الفروق لتصغير تأثير عدم الرد في الموضعين. نستخدم بذكاء المعلومات الإضافية للحصول على خطط كفوء لتقدير تباين المجتمع في الموضع الحالي. تم الحصول على تقديرات للموضع الحالي كحالات خاصة عندما يكون عدم الرد العشوائي في الموضع الأول أو الموضع الثاني. تم عمل دراسات تجريبية لمقارنة أداء التقديرات المقترحة مع القيمة الفعلية للتباين وتقديرات طريقة التناسب عندما تكون الردود كاملة. تم تفسير النتائج وتقديم توصيات ملائمة من خلال دراسات تجريبية.