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EXPONENTIAL METHOD OF IMPUTATION FOR NON-RESPONSE IN SAMPLE SURVEYS

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ABSTRACT

Motivated by a recent work of Gira (2015), a ratio exponential method of imputation has been suggested and their corresponding resultant point estimator for non-response in sample surveys has been explored. Thereafter, an expression of bias and their mean square error are obtained for the suggested estimator upto the first order of large approximation. Further, it is compared with the mean imputation method, ratio imputation method, regression imputation method and estimators given by Singh and Horn (2000), Singh and Deo (2003), Singh (2009), and Gira (2015). The numerical demonstration shows that the suggested estimator is the most efficient estimator.

KEYWORDS

Imputation methods, Bias, Mean square error (MSE), Efficiency, Population Parameters.

2010 Mathematics Subject Classification: 62D05.

1. INTRODUCTION

Non-response is one major problem, which is encountered by practitioners in the field of sample surveys. Determining the appropriate analytical approach in the presence of incomplete survey data due to non-response is a major question for the analysts and researchers, as the inference concerning population parameters can be spoiled if the suitable information about the nature of non-response is not known. A natural question arises what one needs to assume to justify ignoring the incomplete mechanism. Rubin (1976), addressed three concepts: missing at random (MAR), observed at random (OAR) and parameter distribution (PD). Rubin defined “The data are MAR if the probability of the observed missingness pattern, given the observed and unobserved data, does not depend on the value of the unobserved data”. Heitzan and Basu (1996), have distinguished the meaning of missing at random (MAR) and missing completely at random (MCAR) in a very nice way. Many methods are used to minimize the negative impact of non-response in sample surveys. Imputation is such which deals mutually the filling up method of incomplete data for adapting the standard analytic model in statistics. Imputation methods are developed to handle missing data. The term ‘imputation’ refers to the process of assigning one or more values to an items when there is no reported value for that items. These values are either taken directly from values reported by another respondent in the same survey or derived indirectly for a model that relates non-respondents to respondents. Later for the MCAR response mechanism, Satici and Kadilar (2009, 2011) also proposed the ratio estimator in successive sampling under non-response. Singh and Horn (2000), suggested a compromised imputation method. Singh and Deo (2003), Toutenburg *et al.* (2008), Kadilar and Cingi (2008), Singh (2009), Singh *et al.* (2010), Diana and Perri (2010), Gira (2015) and Prasad (2016), have suggested different imputation methods with the aid of an auxiliary variable.

Let us consider a finite population of size N with values $Y_1, Y_2, \ldots Y_N$ of the study variable and values $X_1, X_2, \ldots X_N$ of the auxiliary variable. For the estimate of the population mean $\bar{Y}$, a random sample of size n is drawn according to the procedure of SRSWOR scheme. Assuming the non-response to be random, suppose that there are r response units (y_1, x_1), $(y_2, x_2), \ldots (y_r, x_r)$, and $(n-r)$ non-response units. Let r be the number of responding units out of sampled n units, the set of responding units by R and R^C be the set of non-responding units.

When the response units are observed, it is customary to estimate population mean $\bar{Y}$ by

$$\bar{y}_r = \frac{1}{r}\sum_{i=1}^{r} y_{.i} \tag{1}$$

When the non-response units are missing and imputed values are to be derived for such units.

$$y_{.i} = \begin{cases} y_i & \text{if } i \in R \\ \tilde{y}_i & \text{if } i \in R^c \end{cases} \tag{2}$$

The general point estimator of population mean $\bar{Y}$ takes the form:

$$\tau = \frac{1}{n}\sum_{i=1}^{n} y_{.i} = \frac{1}{n}\left[\sum_{i \in R} y_{.i} + \sum_{i \in R^c} y_{.i}\right] = \frac{1}{n}\left[\sum_{i \in R} y_i + \sum_{i \in R^c} \tilde{y}_i\right] \tag{3}$$

Here, the value denote the imputed value of the study variable corresponding to the ith non-responding units.

2. SOME EXISTING ESTIMATORS

In this section, we discuss the several estimators with imputation for estimating the population mean in sample surveys.

2.1 Mean Imputation Method

Under this method, the resultant point estimator (3) of $\bar{Y}$ is derived as

$$\bar{y}_m = \frac{1}{r}\sum_{i=1}^{r} y_i = \bar{y}_r \tag{4}$$

which is known as the response sample estimators $\bar{y}_r$ of population mean $\bar{Y}$.

The variance of the response sample mean $\bar{y}_r$, is given by

$$Var(\bar{y}_r) = \left(\frac{1}{r} - \frac{1}{N}\right)\bar{Y}^2 C_y^2 \tag{5}$$

2.2 Ratio Imputation Method

Under this method, the resultant point estimator (3) of $\bar{Y}$ is derived as

$$\bar{y}_{rat} = \bar{y}_r \frac{\bar{x}_n}{\bar{x}_r} \tag{6}$$

which is known as the ratio estimator $\bar{y}_{rat}$ of $\bar{Y}$. The MSE of estimator $\bar{y}_{rat}$, is given by

$$MSE\left(\bar{y}_{rat}\right) = Var(\bar{y}_r) + \left(\frac{1}{r} - \frac{1}{n}\right)\bar{Y}^2\left(C_x^2 - 2\rho_{yx} C_y C_x\right) \tag{7}$$

2.3 Regression Imputation Method

Under this method, the resultant point estimator (3) of $\bar{Y}$ is given by

$$\bar{y}_{reg} = \bar{y}_r + \hat{b}\left(\bar{x}_n - \bar{x}_r\right) \tag{8}$$

which is known as regression estimator $\bar{y}_{reg}$ of $\bar{Y}$, where $\hat{b} = \frac{s_{yx}(r)}{s_x^2(r)}$.

The MSE of estimator $\bar{y}_{reg}$, is given by

$$MSE\left(\bar{y}_{reg}\right) = \bar{Y}^2 C_y^2\left[\left(\frac{1}{r} - \frac{1}{N}\right) - \left(\frac{1}{r} - \frac{1}{n}\right)\rho_{yx}^2\right] \tag{9}$$

2.4 Singh and Horn (2000) Estimator

Singh and Horn (2000) suggested a compromised imputation method in survey sampling. Under this method, the resultant point estimators (3) of $\bar{Y}$ is derived as

$$\bar{y}_{sh} = \alpha\bar{y}_r + \left(1 - \alpha\right)\bar{y}_r \frac{\bar{x}_n}{\bar{x}_r} \tag{10}$$

where α is a constant. The optimum value of α is $1 - \rho_{yx}\frac{C_y}{C_x}$.

Now, taking the optimum value of α in (10), we obtained the minimum MSE of $\bar{y}_{sh}$, is given by

$$MSE\left(\bar{y}_{sh}\right)_{opt} = MSE\left(\bar{y}_{rat}\right) - \left(\frac{1}{r} - \frac{1}{n}\right)\left(C_x - \rho_{yx} C_y\right)^2 \bar{Y}^2 \tag{11}$$

2.5 Singh and Deo (2003) Estimator

Singh and Deo (2003) suggested imputation by power transformation in survey sampling. Under this method, the resultant point estimators (3) of the population mean $\bar{Y}$ becomes

$$\bar{y}_{sd} = \bar{y}_r \left(\frac{\bar{x}_n}{\bar{x}_r} \right)^{\beta} \tag{12}$$

where β is a constant. The optimum value of β is $\rho_{yx} \frac{C_y}{C_x}$.

Now, taking the optimum value β in (12), we obtained the minimum MSE of $\bar{y}_{sd}$, given by

$$MSE\left(\bar{y}_{sd}\right)_{opt} = MSE\left(\bar{y}_{rat}\right) - \left(\frac{1}{r} - \frac{1}{n}\right) S_x^2 \left(\frac{S_{yx}}{S_x^2} - \frac{\bar{Y}}{\bar{X}} \right)^2 \tag{13}$$

2.6 Singh (2009) **Estimator**

Singh (2009) suggested a different imputation method in survey sampling. Under this method, the resultant point estimators (3) of the population mean $\bar{Y}$ becomes

$$\bar{y}_{\sin gh} = \frac{\bar{y}_r \bar{x}_n}{\gamma \bar{x}_r + (1-\gamma)\bar{x}_n} \tag{14}$$

where γ is a constant. The optimum value of γ is $\rho_{yx} \frac{C_y}{C_x}$. Now, using the optimum value of γ in equation (14), we get the minimum MSE of the estimator $\bar{y}_{\sin gh}$, given by

$$MSE\left(\bar{y}_{\sin gh}\right)_{opt} = MSE\left(\bar{y}_{rat}\right) - \left(\frac{1}{r} - \frac{1}{n}\right)\left(C_x - \rho_{yx} C_y\right)^2 \bar{Y}^2 \tag{15}$$

2.7 Gira (2015) **Estimator**

Gira (2015) suggested a ratio type imputation in sample surveys. Under this method of imputation, the resultant point estimators (3) of the population mean $\bar{Y}$ becomes

$$\bar{y}_{gira} = \bar{y}_r \frac{\phi - \bar{x}_r}{\phi - \bar{x}_n} \tag{16}$$

where ϕ is a constant. The optimum value of ϕ is $\bar{X}\left(\frac{C_x}{\rho_{yx} C_y} - 1 \right)$. Now, using the optimum value of ϕ in equation (16), the minimum MSE of the estimator $\bar{y}_{gira}$, given by

$$MSE\left(\bar{y}_{\sin gh}\right)_{opt} = Var\left(\bar{y}_r\right) - \left(\frac{1}{r} - \frac{1}{n}\right) \rho_{yx}^2 \bar{Y}^2 C_y^2 \tag{17}$$

3. FORMULATION OF THE PROBLEM

We have suggested a ratio exponential method of imputation for estimating the $\bar{Y}$ in sample surveys. After this suggested imputation method, the data takes form:

$$y_{.i} = \begin{cases} y_i \phi \exp\left(\dfrac{\left(\bar{X} - \bar{x}_r\right)\beta_2(x)}{\left(\bar{X} + \bar{x}_r\right)\beta_2(x) + 2S_x} \right) & if \;\; i\varepsilon R \\ \dfrac{\bar{y}_r}{\bar{x}_r}\left[x_i - \dfrac{n}{n-r}\left(\bar{x}_n - \bar{x}_r\right)\right]\phi \exp\left(\dfrac{\left(\bar{X} - \bar{x}_r\right)\beta_2(x)}{\left(\bar{X} + \bar{x}_r\right)\beta_2(x) + 2S_x} \right) & if \;\; i\varepsilon R^C \end{cases} \tag{18}$$

Under the suggested imputation method, the resultant point estimator (3) of the population mean $\bar{Y}$, given by

$$\zeta = \phi \bar{y}_r \exp\left(\frac{\left(\bar{X} - \bar{x}_r\right)\beta_2(x)}{\left(\bar{X} + \bar{x}_r\right)\beta_2(x) + 2S_x} \right) \tag{19}$$

where ϕ is a suitable chosen constant, such that the MSE of the resultant point estimator is minimum, $\beta_2(x)$ and S_x are the population coefficient of kurtosis and standard deviation respectively.

4. PROPERTIES OF THE SUGGESTED ESTIMATOR ζ

The bias and mean square error (MSE) of the suggested estimator ζ is derived upto the first order of large approximation under the following transformations:

$$\bar{y}_r = \bar{Y}\left(1 + e_y\right) \text{ and } \bar{x}_r = \bar{X}\left(1 + e_x\right) \text{ such that } E\left(e_i\right) = 0,\ \left|e_i\right| < 1 \forall i = y, x .$$

Using the above transformations, the estimator ζ takes the following form:

$$\zeta = \phi \bar{Y}\left(1 + e_y\right)\exp\left[-\frac{1}{2}\theta e_x \left(1 + \frac{1}{2}\theta e_x\right)^{-1} \right] \tag{20}$$

where $\theta = \dfrac{\bar{X}\beta_2(x)}{\bar{X}\beta_2(x) + S_x}$.

Neglecting the higher power terms of e’s, the equation (20) can be written as

$$\zeta - \bar{Y} \cong \bar{Y}\left[\left(\phi - 1\right) + \phi\left(e_y - \frac{1}{2}\theta e_x - \frac{1}{2}\theta e_y e_x + \frac{3}{8}\theta^2 e_x^2 \right) \right] \tag{21}$$

Taking expectation of (21), we obtained the bias of the suggested estimator, given as

$$Bias\left(\zeta\right)=\bar{Y}\left[\left(\phi-1\right)+\frac{1}{8}\theta\phi\left(\frac{1}{r}-\frac{1}{N}\right)\left(3\theta C_x^2-4\rho_{yx}C_yC_x\right)\right] \tag{22}$$

Now, after squaring of (21) and neglecting the higher power terms of e's, we have

$$\left(\zeta-\bar{Y}\right)^2\cong\bar{Y}^2\left[\left(\phi-1\right)+\phi\left(e_y-\frac{1}{2}\theta e_x\right)\right]^2 \tag{23}$$

Taking expectation of (23), we get the MSE of the suggested estimator ζ as

$$MSE\left(\zeta\right)=\bar{Y}^2\left[\left(\phi-1\right)^2+\left(\frac{1}{r}-\frac{1}{N}\right)\phi^2\left(C_y^2+\frac{1}{4}\theta^2C_x^2-\theta\rho_{yx}C_yC_x\right)\right] \tag{24}$$

Differentiating (24) with respect to ϕ and its equating to zero, we get the optimum value of ϕ, is given by

$$\phi_{opt}=\frac{1}{1+\left(\frac{1}{r}-\frac{1}{N}\right)\left(C_y^2+\frac{1}{4}\theta^2C_x^2-\theta\rho_{yx}C_yC_x\right)} \tag{25}$$

After substituting the optimum value of ϕ i.e., ϕ_{opt} in (24), we obtain the minimum MSE of the suggested estimator ζ, given as

$$MSE\left(\zeta\right)_{opt}=\frac{\left(\frac{1}{r}-\frac{1}{N}\right)\left(C_y^2+\frac{1}{4}\theta^2C_x^2-\theta\rho_{yx}C_yC_x\right)}{1+\left(\frac{1}{r}-\frac{1}{N}\right)\left(C_y^2+\frac{1}{4}\theta^2C_x^2-\theta\rho_{yx}C_yC_x\right)}\bar{Y}^2 \tag{26}$$

5. NUMERICAL DEMONSTRATION

The five different real data sets are considered for the sample population between 2% to 50%, response rate between 10% to 90% with different correlation coefficient and computed the MSE of the some existing and suggested estimator ζ. The percent relative efficiency of the suggested estimator engaged in numerical demonstration. The PREs of the suggested estimator ζ with respect to mean imputation method, ratio imputation method, regression imputation method, Singh and Horn (2000) estimator, Singh and Deo (2003) estimator, Singh (2009) estimator and Gira (2015) estimator are obtained as

$$PRE_1=\frac{V(\bar{y}_r)}{MSE(\zeta)_{opt}}\times 100 \tag{27}$$

$$PRE_2=\frac{V(\bar{y}_{rat})}{MSE(\zeta)_{opt}}\times 100 \tag{28}$$

$$PRE_3 = \frac{V(\bar{y}_{reg})}{MSE(\zeta)_{opt}} \times 100 \tag{29}$$

$$PRE_4 = \frac{V(\bar{y}_{sh})}{MSE(\zeta)_{opt}} \times 100 \tag{30}$$

$$PRE_5 = \frac{V(\bar{y}_{sd})}{MSE(\zeta)_{opt}} \times 100 \tag{31}$$

$$PRE_6 = \frac{V(\bar{y}_{\sin gh})}{MSE(\zeta)_{opt}} \times 100 \tag{32}$$

$$PRE_7 = \frac{V(\bar{y}_{gira})}{MSE(\zeta)_{opt}} \times 100 \tag{33}$$

Table 1
Parameters of Data Sets

Parameters	data set 1 [Source:[7]] page 228	data set 2 [Source:[7]] page 422	data set 3 [Source:[7]] page 178	data set 4 [Source:[5]]	data set 5 [Source:[6]]
N	80	24	108	923	3059
n	20	12	16	180	61, 183, 489, 611
r	16	9	12	144	(6, 12, 18, 24), (18, 36, 54, 72), (96, 144, 192, 240), (122, 183, 244, 305, 366, 427, 488, 520, 549)
$\bar{Y}$	51.8264	568.5833	172.3704	436.4345	308582.4
$\bar{X}$	2.8513	568.25	461.3981	11440.498	56.5
C_y	0.3542	0.8901	0.7795	1.7183	1.3783
C_x	0.9484	0.9293	0.6903	1.8645	1.2796
$\beta_2(x)$	1.3005	2.2559	1.6307	18.7208	7.5
$\beta_1(x)$	0.6978	1.6651	1.3612	3.9365	2.4
ρ_{yx}	0.9150	0.9589	0.7896	0.9543	0.677428

Table 2
Mean Square Errors of the Existing and Suggested Estimator

Estimators	Data Set 1	Data Set 2	Data Set 3	Data Set 4
Mean method of imputation ($\bar{y}_r$)	16.8488	17787	1337.3	3296.2
Ratio method of imputation ($\bar{y}_{rat}$)	26.4083	11297	1106.3	2598.2
Regression method of imputation ($\bar{y}_{reg}$)	13.3222	11245	1102.8	2584.8
Singh and Horn [14] Estimator ($\bar{y}_{sh}$)	13.3222	11245	1102.8	2584.8
Singh and Deo [13] Estimator ($\bar{y}_{sd}$)	13.3222	11245	1102.8	2584.8
Singh [15]Estimator $\bar{y}_{\sin gh}$	13.3222	11245	1102.8	2584.8
Gira[2]Estimator ($\bar{y}_{gira}$)	13.3222	11245	1102.8	2584.8
Suggested Estimator (ζ)	3.0731	7431.7	788.2445	989.4156

Table 3
Percent Relative Efficiencies of the Suggested Estimator ζ Over the Estimators $\bar{y}_r$, $\bar{y}_{rat}$, $\bar{y}_{reg}$, $\bar{y}_{sh}$, $\bar{y}_{sd}$, $\bar{y}_{\sin gh}$, and $\bar{y}_{gira}$ respectively under the Different Data Set

Data set	PRE_1	PRE_2	PRE_3	PRE_4	PRE_5	PRE_6	PRE_7
1	548.274	859.347	433.516	433.516	433.516	433.516	433.516
2	239.340	152.006	151.312	151.312	151.312	151.312	151.312
3	169.654	140.344	139.905	139.905	139.905	139.905	139.905
4	333.143	262.599	261.249	261.249	261.249	261.249	261.249

Table 4
Percent Relative Efficiencies of the Suggested Estimator ζ Over the Estimators $\bar{y}_r$, $\bar{y}_{rat}$, $\bar{y}_{reg}$, $\bar{y}_{sh}$, $\bar{y}_{sd}$, $\bar{y}_{\sin gh}$ and $\bar{y}_{gira}$ respectively for Data Set 5

n	r	PRE_1	PRE_2	PRE_3	PRE_4	PRE_5	PRE_6	PRE_7
61	4	208.725	131.408	119.103	119.103	119.103	119.103	119.103
	6	192.895	123.903	112.924	112.924	112.924	112.924	112.924
	12	177.064	120.532	111.536	111.536	111.536	111.536	111.536
	18	171.787	123.561	115.886	115.886	115.886	115.886	115.886
	24	169.149	128.209	121.693	121.693	121.693	121.693	121.693
183	12	177.064	111.303	100.837	100.837	100.837	100.837	100.837
	18	171.787	110.103	100.286	100.286	100.286	100.286	100.286
	36	166.510	112.926	104.398	104.398	104.398	104.398	104.398
	54	164.752	117.947	110.498	110.498	110.498	110.498	110.498
	72	163.872	123.572	117.158	117.158	117.158	117.158	117.158
489	90	163.344	108.978	100.326	100.326	100.326	100.326	100.326
	96	163.212	109.599	101.067	101.067	101.067	101.067	101.067
	144	162.553	114.906	107.323	107.323	107.323	107.323	107.323
	192	162.223	120.603	113.980	113.980	113.980	113.980	113.980
	240	162.025	126.581	120.940	120.940	120.940	120.940	120.940
611	117	162.857	108.655	100.029	100.029	100.029	100.029	100.029
	120	162.817	108.902	100.322	100.322	100.322	100.322	100.322
	122	162.791	109.068	100.518	100.518	100.518	100.518	100.518
	183	162.272	114.406	106.788	106.788	106.788	106.788	106.788
	244	162.012	120.146	113.483	113.483	113.483	113.483	113.483
	305	161.856	126.210	120.537	120.537	120.537	120.537	120.537
	366	161.753	132.585	127.943	127.943	127.943	127.943	127.943
	427	161.679	139.275	135.710	135.710	135.710	135.710	135.710
	488	161.623	146.297	143.858	143.858	143.858	143.858	143.858
	520	161.599	150.119	148.292	148.292	148.292	148.292	148.292
	549	161.580	153.669	152.410	152.410	152.410	152.410	152.410

6. ANALYSIS OF NUMERICAL DEMONSTRATION

From Tables (1-4), the following interpretation can be read out:

1. From Table 1 presents the parameters of the five data sets for different correlation coefficient. We are taking different values for n and r .
2. From Table 2 it is clear that the MSE of the suggested estimator ζ is less than the other compared estimators for given data sets.
3. From Table 3 it is observed that for the sample population between 15% to 40%, response rate between 75% to 80% with different correlation coefficient, the suggested estimator is more efficient than compared to other estimators.
4. From Table 4 it is found that
   (a) For a 2% sample population with response rate between 6% to 40%, the PREs of the suggested estimator ζ with respect to the other existing estimators like as the mean imputation method remains 169.149% to 192.895%; the ratio imputation method remains 120.532% to 128.209%; the regression imputation method, Singh and Horn ($\bar{y}_{sh}$) estimator, Singh and Deo ($\bar{y}_{sd}$) estimator, Singh ($\bar{y}_{\sin gh}$)and Gira ($\bar{y}_{gira}$) estimator remain 111.536% to 121.693%.
   (b) For a 6% sample population with response rate between 6% to 40%, the PREs of the suggested estimator ζ with respect to the other existing estimators like as the mean imputation method remains 163.872% to 171.787%; the ratio imputation method remains 110.103% to 123.572%; the regression imputation method, Singh and Horn ($\bar{y}_{sh}$) estimator, Singh and Deo ($\bar{y}_{sd}$) estimator, Singh ($\bar{y}_{\sin gh}$) estimator and Gira ($\bar{y}_{gira}$) estimator remain 100.286% to 117.158%.
   (c) For a 16% sample population with response rate between 18% to 50%, the PREs
   of the suggested estimator ζ with respect to the other existing estimators like as the mean imputation method remains 162.025% to 163.212%; the ratio imputation method remains 109.599% to 126.581%; the regression imputation method, Singh and Horn ($\bar{y}_{sh}$) estimator, Singh and Deo ($\bar{y}_{sd}$) estimator, Singh ($\bar{y}_{\sin gh}$) estimator and Gira ($\bar{y}_{gira}$) estimator remain 101.067% to 120.940%.
   (d) For a 20% sample population with response rate between 19% to 90%, the PREs of the suggested estimator ζ with respect to the other existing estimators like as the mean imputation method remains 161.580% to 162.791%; the ratio imputation method remains 109.068% to 153.669%; the regression imputation method, Singh and Horn ($\bar{y}_{sh}$) estimator, Singh and Deo ($\bar{y}_{sd}$) estimator, Singh ($\bar{y}_{\sin gh}$) estimator and Gira ($\bar{y}_{gira}$) estimator remain 100.518% to 152.410%.

7. CONCLUSIONS

In this paper, a ratio exponential method of imputation has been suggested and their corresponding resultant point estimator for non-response in sample surveys has been explored. Based on the analysis of numerical demonstration, it is observed that the suggested estimator is more efficient than the mean imputation method, ratio imputation method, regression imputation method and the estimators are given by Singh and Horn (2000), Singh and Deo (2003), Singh (2009) and Gira (2015).

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