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A Study of Politz-Simmon Estimator under Non-cooperation

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SUMMARY

It is known that the Politz-Simmon [5] estimator adjusts the non-response bias due to the non-availability of the selected respondents at home during the period of survey, by classifying the available responses into six groups according to their availability at home during the previous week, and employing appropriate weighting procedures. The estimator is based on the premise that the selected respondents available at home, necessarily cooperate with the enumerator, which however may not be true. An attempt has therefore, been made in this article to study the non-response bias in the Politz-Simmon estimator taking into account the possible non-cooperation from the selected respondents who are, though, available at home yet may be busy otherwise.

Key words : Non-Response bias, Total non-response, Weighting classes, Response probability, Politz-Simmon estimator.

1. Introduction

There are generally two types of errors in the sample estimates namely, the Sampling Errors and the Non-Sampling Errors. The former arises due to fact that only the part of the population is being used to estimate the population parameters where as the latter arises, primarily, due to the errors at the stages of observation, ascertainment and processing of the data. One of the major source of non-sampling errors is the non-response which occurs due to the inaccessibility of the selected sampling units, the non-availability of the respondents at home, inability to answer certain questions posed to the respondents and due to the total refusal by some of them. Also, there could be either, total non-response from the respondents when information on none of the items pertaining to an individual respondent can be obtained or there could be item non-response when information is not available only on certain items of the schedule enquiry.

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To compensate for the distortion in the representativeness of the sample due to total non-response Durbin [3] suggested the use of weighting adjustments, by increasing the weights of those respondents who respond with lower probability, so that these may represent, to the extent possible, the characteristics of non-respondents. The weighting procedures, of course, employ the stratification of entire population into a set of weighting classes where the weights are proportional to the inverse of the response rate in the classes. In order to compute these response rates, the number of respondents in each weighting class need to be determined. It must be pointed out that in case the weights are to be estimated from within the sample only, one cannot compensate for the coverage errors which are due to the exclusion of certain units from the domain of the survey.

The problem of non-response has been investigated by several workers who have attempted to develop procedures of estimation for reducing the Non-response bias. The methods to control Non-response bias by Hansen and Hurwitz [4] through sub-sampling approach, the Politz- Simmon [5] techniques for non-response situations eliminating the need for call backs, Anderson [1], Cassel, Sarndal and Wretman [2] estimators, corrected for non-response bias and based on response probabilities, are some attempts in this direction.

2. *Effect of Non-Cooperation of Respondents Available at Home on Politz-Simmon Estimator*

Politz-Simmon [5] estimator adjusts the total non-response bias due to the respondents not available at home, by classifying the entire population into six weighting classes corresponding to the availability of selected respondents, once out of six days, twice out of six days, and so on, upto all the six days during the past week and then, using the appropriate weighting procedures. It is, however, assumed that the class corresponding to the hard core, i.e., the respondents who respond with probability zero, is absent. Also, the procedure assumes that all those persons available at home during the survey visit, necessarily co-operate with the enumerator and provide him response on the desired variables. This assumption is an over simplification of the realistic situation.

Infact, the respondents even when available at home may be busy in certain domestic chores or due to the presence of guests, children's examination, or any other social/domestic reasons, may refuse to co-operate with the enumerator at the time of visit. Probably, such individuals would readily respond during the next visit. Ofcourse, some of them may not at all agree to co-operate. Hence, the structure of the weighting class changes, which is bound to affect the performance of Politz-Simmon estimator.

In Politz-Simmon scheme, the probability of an individual being available at home during the previous week is denoted by P_{ji} (H) which takes the values 1/6, 2/6, ..., 6/6, respectively, depending upon whether j-th individual belongs to the i-th Home-availability class, 'i' varying from 1 to 6. Let us denote by $P_{ji}(W \mid H)$, the conditional probability of j-th individual, given that i-th is available at home, to be willing to co-operate. It is obvious that the response is obtained only when an individual is available at home and is willing to co-operate. Thus, the probability of response, $P_{ji}(R)$ for the individual in class 'i' can, then, be written as

$$
\begin{aligned}
P_{ji}(R) &= P_{ji}(W \cap H) \\
&= P_{ji}(W \mid H) \,.\, P_{ji}(H) \\
& \qquad i = 1, 2, \ldots, 6 \\
& \qquad j = 1, 2, \ldots, N
\end{aligned}
$$

where $P_{ji}(W \cap H)$ is the probability that the j^{th} individual is available at home and is also willing to cooperate with the enumerator at the time of visit.

Since the weighting of the respondents in each weighting class has to be done according to the response rates, the distribution of response assumes special significance. Level of response can assume only discrete integral values 0, 1, 2, ..., 6 with $0 \le P_{ji}(R) \le P_{ji}(H)$. It is obvious that when $P_{ji}(H) > 0$, every structure of $P_{ji}(R) = P_{ji}(W \cap H)$ has to be determined in such a manner that,

$$0 \le P_{ji}(W \mid H) = P_{ji}(W \cap H)/P_{ji}(H) \le 1$$

For abbreviated notation, we shall use $P_{ji}(H) = h$ and $P_{ji}(R) = r$.

Reasons for this structure are obvious. An individual who is available at home say five times out of six, may be willing to co-operate only on say three occasions, i.e., he may belong to the class 'i' with $P_{ji}(H) = 5/6$ in the Politz-Simmon set-up but he belongs to the weighting class 'i' with $P_{ji}(R) = 3/6$ due to lack of cooperation from him. This shift of j^{th} individual from a given at-home-availability class to another 'lower' response class affects the behaviour of the Politz- Simmon estimator.

The Politz-Simmon estimator,

$$\overline{Y}_1 = (1/n) \sum_{j}^{N} (Y_j/h) \text{ where } h = i/6 \text{ for } j \in i$$

adjusts the bias due to not at home. Since the respondents, even when available at home could still be non-cooperative and assuming that the enumerator could still enquire his availability at home and respondability during the past six days, we have seven weighting classes, corresponding to i=0, 1, 2, ..., 6 rather than six, present in Politz-Simmon scheme. In such a situation we define an analogus estimator,

$$\overline{Y}_2 = (1/n) \sum_{j}^{N} (Y_j/r) \text{ where } r \leq h$$

$\overline{Y}_1$ assumes that all persons available at home are also willing to cooperate. In $\overline{Y}_2$, there is much greater degree of non-response, as some of the individuals who may be available at home, may not be willing to cooperate. In this case, we also have the situation of zero response, which is assumed to be non-existant in Politz-Simmon scheme and thus, the concerned units are totally removed from the sampled population. These factors should lead to greater bias.

3. *Bias and Variance*

The derivations of bias and variance follow the well known arguments as given by Sukhatme, Sukhatme, Sukhatme and Asok [7]

$$B(\overline{Y}_1) = -(1/N) \sum_{j}^{N} Y_j \; (1-h)^6$$

$$B(\overline{Y}_2) = -(1/N) \sum_{j}^{N} Y_j (1-r)^6$$

Since, $r \leq h$ holds, we have, $|B(\overline{Y}_2)| \geq |B(\overline{Y}_1)|$. Ofcourse, this increased bias in $\overline{Y}_2$ is due to the reduction in the level of response.

The variance expressions for the two cases are given below :

$$V_1 = V(\overline{Y}_1) = (1/n) [(1/N) \sum_{j}^{N} Y_j^2 \sum_{k}^{6} \left(\frac{6}{k}\right) {}^6C_k \, h^k (1-h)^{6-k} - \{(1/N) \sum_{j}^{N} Y_j \; (1-(1-h)^6) \}^2]$$

$$= (1/n)\ [(1/N) \sum_{j}^{n} Y_j^2 Q_{1ji} - T_1^2]$$

where $$Q_{1ji} = \sum_{k}^{6} \left(\frac{6}{k}\right) {}^6C_k\, h^k (1-h)^{6-k}$$

and $$T_1 = (1/N) \sum_{j}^{N} Y_j\ [1-(1-h)^6]$$

$$V_2 = V(\overline{Y}_2) = (1/n)\,[(1/N) \sum_{j}^{N} Y_j^2 \sum_{k}^{6} \left(\frac{6}{k}\right) {}^6C_k\, r^k (1-r)^{6-k}$$

$$- [(1/N) \sum_{j}^{N} Y_j (1-(1-r)^6)]^2$$

$$= (1/n)\ [(1/N) \sum_{j}^{N} Y_j^2\ Q_{2ji} - T_2^2]$$

where $$Q_{2ji} = \sum_{k}^{6} \left(\frac{6}{k}\right) {}^6C_k\, r^k (1-r)^{6-k}$$

and $$T_2 = (1/N) \sum_{j}^{N} Y_j\,[1-(1-r_{ji})^6]$$

Now, $r \leq h$ implies that $(1-r) \geq (1-h)$ i.e., $(1-r)^6 \geq (1-h)^6$ which means that, $1-(1-r)^6 \leq 1-(1-h)^6$ and hence, $T_2 \leq T_1$.

Now, the expressions of Q_{1ji} and Q_{2ji} cannot be as such compared algebraically. It, however, appears that the difference in the two terms Q_{1ji} and Q_{2ji} may be due to the re-distribution of the units over the various lower order weighting classes due to non-cooperation of at-home-available respondents who may, now, respond with a lower probability. In case the redistribution is not much, Q_{1ji} and Q_{2ji} may not differ much and thus we, normally expect that $V(\overline{Y}_1)$ will be more or less equal to $V(\overline{Y}_2)$. In case, the redistribution is large, for classes having larger Y values, $V(\overline{Y}_2)$ could be less than $V(\overline{Y}_1)$.

4. *Empirical Study of the Behaviour of the Politz-Simmon Estimator*

In order to compare the behaviour of Politz-Simmon estimator with respect to its bias, variance and mean square error under the situation of non-cooperation from the At-Home-Available (AHA) respondents against the situation when there is full co-operation of AHA respondents, we have selected three types of artificial populations, 'I' : heterogenous having defined strata boundaries, with stratification done according to the probability of At-Home- Availability, 'II' : heterogenous population having no defined strata boundaries and 'III' : homogenous population with no defined strata boundaries. The range of Y values has been arbitrarily chosen between 0 and 100 assuming that any real population could be scaled down to 0 to 100 range.

The pattern of response after allowing for the non-cooperation, is not known beforehand. However, a respondent who is available at home for say 'i' times may have a busy schedule on certain occasions during these 'i' availability at home and thus the response probability is a discrete distribution in the range $0 \leq R \leq i/6$.

In this study, we assume a uniform discrete distribution for R within $0 \leq R \leq i/6$. Though such a situation is the most extreme, in the sense that a respondent would just not refuse randomly, and instead may put forward an explanation for his refusals in terms of busy schedule of his engagements, etc., yet the assumption serves the purpose because if the behaviour of P-S estimator could be characterised for random response, its behaviour for less extreme situation could probably be anticipated.

The size of weighting class or the AHA class is also important. The different size distributions over the AHA classes would give different weights to the bias, variance and mean square error for different AHA classes, resulting into different behaviour of estimator. Consequently, in this study, we consider the two extremes, of negatively skewed size distribution (denoted by 'n') having higher class size for higher Y-values and smaller class size for smaller Y- values and the positive skewed size distribution (denoted by 'p') having larger class sizes for smaller Y-values and smaller class sizes for larger Y-values. Between the two extremes, we also consider the mid-way size distribution having same class size (denoted by 'c') for all the six AHA classes.

As a result of non-cooperation on the part of respondent, there is always a possibility of zero response, in which case, no information can be obtained from the respondent. This causes a bias due to the fact that one group of respondents go out of the domain of the survey. Ofcourse, in case the average Y for this group is not much different from the average Y from the group who is responding (with whatever response probability), the bias due to zero response may not be much. The situation where zero response is possible has been termed 'A' in this study.

In order to know as to what differences are caused by this zero- response situation, vis-a-vis non-zero response situations we consider two more situations, where zero-response is not permitted namely 'B', where response probability, as a result of non-cooperation, is limited to the range $1/6 \leq R \leq i/6$, assuming a uniform discrete distribution for the response behaviour and 'C', when by making special efforts and using better field survey techniques, the group of zero responses is shifted to the response class with the probability 1/6.

It has been pointed out that the bias B_1, of estimator, $\overline{Y}_1$, i.e., the Politz-Simmon estimator with full co-operation is always, numerically (in absolute terms) less than or equal to the bias of $\overline{Y}_2$. Also, it was argued that one major cause of the difference in the variance of the two cases, is probably due to the difference between Q_{1ji} and Q_{2ji}, which arises from the shift of responses from higher AHA-classes to the lower response classes, as a result of non-cooperation resulting into lower response rates due to busy schedule, etc. Thus, it appears that the best practical situation for the application of $\overline{Y}_2$ could be, the population types having higher Y-values in the lower response classes and the lower Y-values in the higher response classes. These types of populations are represented by 'I'.

The various populations of each type and class-size were randomly generated, obtaining random numbers within the specified range of Y- values in each class and with replacement. The populations generated alongwith the Y-values and various response classes have been presented in Table-1. It may be noted that the values of Y-variable are different even for the same specified range of Y-values due to the random generation. Infact, each random generation of Y-values provide a population randomly sampled from the super population, represented by the population type and therefore even if the overall characteristics of the population type is the same, the bias, the variance and the mean square error of the estimators would be different. Also, even for the same sampled population from a given population type, the random generation of response behaviour, further results in differences between bias, variance and mean squares.

Thus, we compare the differences in bias, variance and mean squares for the same randomly generated population from a given population type and given class-size distribution, but differing in the response behaviour. This will ensure

Table 1. Different Population Types Considered for the Situations I, II, III, and with Population Size, N = 30

Population Type	Size Type	At-Home Availability Weighting Class	1/6	2/6	3/6	4/6	5/6	6/6
		Response Prob. class	0-1/6	0-2/6	0-3/6	0-4/6	0-5/6	0-6/6
I	A	Range of Y-values	45-100	27-45	18-27	9-18	4-9	0-4
		Class size	2	3	5	6	6	8
	B	Range of Y-values	45-100	27-45	18-27	9-18	4-9	0-4
		Class size	8	6	6	5	3	2
	C	Range of Y-values	45-100	27-45	18-27	9-18	4-9	0-4
		Class size	5	5	5	5	5	5
II	A	Range of Y-values	1-100	1-100	1-100	1-100	1-100	1-100
		Class size	2	3	5	6	6	8
	B	Range of Y-values	1-100	1-100	1-100	1-100	1-100	1-100
		Class size	8	6	6	5	3	2
	C	Range of Y-values	1-100	1-100	1-100	1-100	1-100	1-100
		Class size	5	5	5	5	5	5
III	A	Actual Y-values	44, 42	41, 43, 40	41, 42, 43, 44, 41	42, 42, 41, 44, 41, 42	43, 44, 40, 41, 42, 43	44, 42, 41, 40, 41, 42, 43, 44
		Class size	2	3	5	6	6	8
	B	Actual Y-values	40, 42, 41, 43, 40, 41, 42, 43	44, 41, 42, 42, 41, 44	41, 42, 43, 44, 40, 41	42, 43, 44, 42, 41	40, 41, 42	43, 44
		Class size	8	6	6	5	3	2
	C	Actual Y-values	40, 42, 41, 43, 40	41, 42, 43, 44, 41	42, 42, 41, 44, 41	42, 43, 44, 42, 41	42, 43, 44, 42, 41	40, 41, 42, 43, 44
		Class size	5	5	5	5	5	5

that the differences in bias etc. within each population type, is only due to different response behaviour.

The change in response behaviour is reflected in the shift of the respondents from the earlier AHA-class size distribution, to a new response class size-distribution termed as revised class size distribution. In order to characterize the shifts, we have measured the absolute difference $|Q_1 - Q_2| = \sum |Q_{2ji} - Q_{1ji}|$ within each class so that negative values do not cancel out positive values and obtain an average m_1 of these values. It may be noted that when m_1=0, there is no shift of the respondent from the higher AHA class to lower response class. Also when m_1 is high, it indicates greater shift approximately. Thus, though m_1 may not be the best indicator possible for measuring this shift, it does throw some light on this aspect.

The summary results of the typical four simulations for each of the twenty seven combinations, resulting into markedly different values of m_1 only are presented in Tables 2.1 to 2.3.

Table 2. The Relation between Class-Size-Indicator, m_1, Bias, Variance and MSE differences, M_2–M_1 (Situation and Population wise)

2.1 Situation–A

Simulation	Population type & size		m_1	$B_1 - B_2$	$V(\bar{Y}_2)-V(\bar{Y}_1)$	$M_2 - M_1$ $(MSE_2 - MSE_1)$
1	1.	I, p	3.1	2.0	51	63
2		---	4.0	6.4	–385	–317
3			4.2	5.2	–313	–265
4			5.5	8.1	–792	–694
Correlation with m_1 :				0.87	–0.86	0.86
1	2.	I, n	4.1	9.6	–488	–262
2		---	4.6	10.4	–813	–577
3			4.9	16.1	–2283	–1801
4			5.0	14.1	–1403	–1005
Correlation with m_1 :				0.86	–0.88	–0.89
1	3.	I, c	3.0	6.4	–697	–599
2		---	4.0	7.0	–260	–250
3			4.7	8.0	–632	–497
4			5.3	12.0	–1249	–998
Correlation with m_1 :				0.86	–0.58	–0.50

1	4.	II, p	3.9	13.5	1256	1483
2		---	4.0	14.9	1516	1788
3			4.7	9.9	1800	1932
4			4.9	23.4	328	296
Correlation with m_1 :				0.85	–0.86	–0.91
1	5.	II, n	3.6	14.4	–290	61
2		---	3.9	9.0	17	187
3			4.4	15.7	–441	–37
4			4.7	16.1	–446	–26
Correlation with m_1 :				0.50	–0.57	–0.52
1	6.	II, c	3.3	10.6	976	1185
2		---	3.4	18.0	1137	1628
3			3.6	10.4	988	1193
4			5.1	29.0	–1596	–487
Correlation with m_1 :				0.66	–0.80	–0.78
1	7.	III, p	3.9	3.5	777	199
2		---	4.6	12.7	613	810
3			4.8	11.9	483	658
4			6.3	16.8	503	832
Correlation with m_1 :				0.89	–0.74	0.25
1	8.	III, n	3.9	12.1	131	389
2		---	4.1	13.7	–256	58
3			4.4	15.5	–250	131
4			4.4	10.9	151	369
Correlation with m_1 :				0.16	–0.19	–0.17
1	9.	III, c	4.0	8.3	337	456
2		---	4.5	13.7	132	404
3			5.0	18.1	124	561
4			5.4	14.4	391	687
Correlation with m_1 :				0.77	0.09	0.86

2.2 Situation–B

Simu-lation	Population type & size		m_1	$B_1 - B_2$	$V(\overline{Y}_2)-V(\overline{Y}_1)$	$M_2 - M_1$ $(MSE_2 - MSE_1)$
1	10.	I, p	3.2	1.3	23	30
2		- - -	3.4	1.6	19	28
3			3.7	1.3	15	21
4			3.8	1.1	15	20
Correlation with m_1 :				–0.47	–0.99	–0.97
1	11.	I, n	1.2	1.4	55	80
2		- - -	1.3	1.2	54	74
3			1.4	0.8	8	22
4			1.8	2.5	70	116
Correlation with m_1 :				0.84	0.40	0.58
1	12.	I, c	2.2	1.1	63	76
2		- - -	2.8	1.7	24	45
3			2.9	1.2	33	47
4			3.4	2.2	30	58
Correlation with m_1 :				0.82	–0.79	–0.55
1	13.	II, p	3.1	3.5	1180	1204
2		- - -	3.2	6.3	1117	1179
3			3.6	5.9	1588	1647
4			3.7	4.1	1200	1232
Correlation with m_1 :				0.13	0.52	0.51
1	14.	II, n	1.1	2.1	945	975
2		- - -	1.5	7.8	959	1117
3			1.7	4.3	861	933
4			2.1	6.0	1410	1520
Correlation with m_1 :				0.51	0.70	0.74
1	15.	II, c	2.0	7.1	1458	1664
2		- - -	2.1	5.5	854	915
3			2.8	5.0	1509	1573
4			2.9	7.7	1844	1947
Correlation with m_1 :				0.02	0.66	0.55
1	16.	III, p	3.3	2.3	623	635
2		- - -	3.3	2.5	831	844
3			3.7	4.1	960	988
4			3.7	2.4	676	688
Correlation with m_1 :				0.51	0.29	0.30

1	17.	III, n	1.4	3.8	416	465
2		- - -	1.5	2.3	395	422
3			1.8	2.8	499	533
4			2.0	3.0	651	687
Correlation with m_1 :				–0.28	0.96	0.93
1	18.	III, c	2.0	5.4	764	825
2		- - -	2.5	2.9	491	517
3			2.9	2.8	616	641
4			3.1	2.7	621	645
Correlation with m_1 :				–0.91	–0.48	–0.55

2.3 Situation–C

Simu-lation	Population type & size		m_1	$B_1 - B_2$	$V(\overline{Y}_2)-V(\overline{Y}_1)$	$M_2 - M_1$ $(MSE_2 - MSE_1)$
1	19.	I, p	3.0	1.5	28	35
2		- - -	3.5	1.3	21	27
3			3.9	2.2	30	42
4			4.0	2.6	31	44
Correlation with m_1 :				0.81	0.39	0.58
1	20.	I, n	1.6	2.3	59	97
2		- - -	1.8	2.1	84	119
3			2.0	3.1	60	114
4			2.1	2.9	63	112
Correlation with m_1 :				0.77	–0.07	0.64
1	21.	I, c	2.1	2.6	41	73
2		- - -	2.8	1.4	38	53
3			3.2	2.1	45	69
4			3.3	2.6	19	51
Correlation with m_1 :				–0.09	–0.46	–0.55
1	22.	II, p	3.1	8.5	2457	2551
2		- - -	3.5	9.4	3198	3312
3			3.7	8.5	2984	3080
4			4.3	9.6	3299	3417
Correlation with m_1 :				0.70	0.82	0.83

1	23.	II, n	0.9	4.0	853	915
2		---	1.3	3.2	530	577
3			1.3	5.9	1083	1185
4			1.9	6.3	1433	1546
Correlation with m_1 :				0.69	0.74	0.74
1	24.	II, c	2.5	7.6	2078	2197
2		---	3.1	7.1	1777	1884
3			3.2	5.5	1827	1900
4			3.3	9.5	2827	2993
Correlation with m_1 :				0.02	0.25	0.24
1	25.	III, p	3.7	4.3	831	862
2		---	3.8	4.7	827	862
3			3.9	5.5	1034	1079
4			3.9	5.4	892	937
Correlation with m_1 :				0.93	0.59	0.62
1	26.	III, n	1.5	5.1	570	643
2		---	1.7	4.9	529	597
3			1.9	5.0	586	658
4			2.0	6.1	568	662
Correlation with m_1 :				0.65	0.32	0.52
1	27.	III, c	2.4	5.1	632	690
2		---	2.5	4.7	517	568
3			2.8	4.6	654	703
4			2.9	5.5	793	856
Correlation with m_1 :				0.22	0.71	0.69

The results indicate that there is generally a positive correlation between the class-size shift indicator, m_1 and the bias difference $B_1 - B_2$, meaning thereby that greater the m_1, larger the bias difference shall be. The correlation between the shift indicator and the mean square error difference is negative in I(A)p, I(A)n, II(A)p, II(A)c and I(B)p and it is positive in III(A)c, III(B)n and II(C)p, whereas in all other cases the correlations are poor. It is worth noting that the estimator $\overline{Y}_2$ does well under I(A)p, I(A)n and I(A)c especially when the shift indicator is large. Though the bias is large, but from the mean square error differences, it appears that the negatively skewed class size distribution is well suited to $\overline{Y}_2$. Under I(B)p, I(B)n and I(B)c and also under I(C)p, I(C)n and I(C)c, the estimator $\overline{Y}_2$ has slightly more bias, more variance and more mean square error than $\overline{Y}_1$, yet the differences are not large. The class size 'n' the negatively skewed has largest bias, variance etc. in each of the two situations.

Population type II in all the three situations have very large variance and mean square error differences. It is quite logical to expect this result, as the best situation was anticipated to be the population of type 'I' having distinct strata boundaries as the stratified sampling with suitable allocation is well known to provide better estimators with lower standard errors and the gains are especially pronounced when the population is heterogenous. The population type 'III' in all the three situations, fall midway between type 'I' and 'II' in respect of the mean square error differences. It may specially be noted that the population of type 'III' is very homogenous and the weighting adjustments do not decrease the variance and mean square error. Instead, if any missing value is substituted by the average of the response set, the overall standard errors would be greatly reduced and as such, the imputation procedures may be recommended in such cases.

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