TWO EFFICIENT RANDOM IMPUTATION PROCEDURES

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1. Introduction

Total nonresponse and item nonresponse are both common in surveys. Total nonresponse arises from refusal or inability to participate and from the not-at-homes or not found. Item nonresponse on single questions, also called non-ascertained or not answered, may be due to refusals, to "don't knows", to omissions, or to voided answers. This paper is concerned with the efficiency of some methods of adjusting for such missing data. Other reasons for adjustments include noncoverage and post-stratification; our treatment does not cover them explicitly but has implications for them also.

Weighting and imputation are two alternative methods for increasing the weights of the responses in the sample in efforts to compensate for the missing nonresponses. The two methods have the same average or the same "expected" value, hence the same expected residual biases that adjustments may not remove entirely. When based only on samples of the responses, imputation gives rise to an additional source of sampling variation, which we term the imputation variance. The reduction of this imputation variance is our chief objective here.

For total nonresponses, uniform weighting within classes of the sample may be used to avoid the imputation variance, though imputation of a subsample of respondents' records may be used instead to restore self-weighting cases. But for item nonresponses, each item would need a different set of weights, and to avoid that complexity, imputation is generally preferred. Since we are concerned with imputation variance, we concentrate on item nonresponses. However, the results have implications also for total nonresponses and for other forms of adjustments.

For simple formulation we assume epsem selection and self-weighting for the original sample, but extensions to unequal probabilities and weights are possible.

Many of the imputation procedures used to assign values for missing responses start with a division of the sample into classes based on characteristics known for both the respondents and nonrespondents to the item in question. The imputation classes are formed to meet two aims: one that the missing responses can be hopefully treated as if missing at random within the classes and the other that the values for the item be relatively homogeneous within the classes. Homogeneity is usually only relative, and the randomness of missing values is needed but not believed. When the imputation classes have been determined, there are various ways of carrying out the imputations. One way is by mean-value imputation in which all the nonrespondents in a class are assigned the class mean for the respondents. Another way is a "hot-deck" method in which sample records are considered sequentially, with a nonrespondent being assigned the value of the preceding respondent in the same class. If the records are in random order, this "hot-deck" method is equivalent to the selection within each class of an unrestricted sample (simple random sample with replacement) of size equal to the number of nonrespondents from the respondents, and then the random assignment of the sampled values to the nonrespondents (ignoring the start-up problem, or treating the list of records as a circular one). We will consider only this simple case here; see Bailar and Bailar (1978) for a treatment of the case where the records are serially correlated.

The major disadvantage of the mean-value imputation method is that it distorts the distribution of the item: the concentration of all the imputed values at the class means creates spikes in the distribution, and the element variance is reduced artificially and underestimated. For this reason, some method of assigning respondents' values to nonrespondents is often preferred. However, the selection of respondents for these methods gives rise to additional variance in the survey estimators. We examine the effect of the imputation variance on the precision of the estimator of the class mean, and propose two main procedures for sampling the respondents that reduce the additional variance. One procedure is improved sample design through selection of respondents without replacement (Section 3) and with stratification of responses (Section 4). The second concerns increasing the size of the sample base by multiple imputation and we present two techniques for doing this (Section 5).

2. Imputation Variance

In order to examine the variance impact of various methods of imputing values for missing responses we consider the estimation of a population mean from an epsem sample of size n, comprising r responses and m missing values, within a single imputation class. Throughout we take the variances conditional on fixed r and m. For simplicity we assume that the population comprises fixed response and nonresponse strata.

The overall sample mean of respondents' values and nonrespondents' missing values is given by

$$\bar{y} = \Sigma y_i/n = (\Sigma y_{ri} + \Sigma y_{mi})/n$$

$$= (r\bar{y}_r + m\bar{y}_m)/n = \bar{r}\bar{y}_r + \bar{m}\bar{y}_m$$

where $\bar{r} = r/n$ and $\bar{m} = m/n$ are the response and nonresponse rates respectively. The variance of $\bar{y}$ is given by

$$V(\bar{y}) = V_1E_2(\bar{y}) + E_1V_2(\bar{y})$$

where E_2 and V_2 are the expectation and variance of $\bar{y}$ over the imputation scheme conditional on the initial sample, and E_1 and V_1 are the corresponding operators for the initial sampling.

For the mean-value imputation scheme, $y_{mi} = \bar{y}_r$ and hence $\bar{y} = \bar{y}_r$; for the uniform weighting adjustment scheme $\bar{y} = \bar{y}_r$ also. For these schemes, and indeed for any schemes for which $\bar{y}_m = \bar{y}_r$, $V_2(\bar{y}) = 0$, and thus

$$V(\bar{y}) = V_1(\bar{y}_r). \tag{1}$$

For any compensation scheme that selects m respondents by epsem sampling, either to serve as donors of values for missing item responses in imputation or to receive additional weights to represent unit nonrespondents in weighting adjustments, $E_2(\bar{y}_m) = \bar{y}_r$ and hence $E_2(\bar{y}) = \bar{y}_r$. Also, $V_2(\bar{y}) = V_2(r\bar{y}_r + m\bar{y}_m) = m\, V_2(\bar{y}_m)$. Thus, for such schemes,

$$V(\bar{y}) = V_1(\bar{y}_r) + \bar{m}^2 E_1 V_2(\bar{y}_m). \tag{2}$$

A comparison of equations (1) and (2) shows that $V(\bar{y})$ is minimized by using an imputation scheme in which $\bar{y}_m = \bar{y}_r$, such as mean-value imputation, and that the proportionate increase in variance from using a random epsem imputation scheme is given by

$$I = \bar{m}^2 E_1 V_2(\bar{y}_m)/V_1(\bar{y}_r) .$$

In the rest of the paper we examine the magnitude of the proportionate increase I for various random imputation schemes. We will henceforth assume that the initial sample is a SRS and that the population size is sufficiently large compared to the sample size for the finite population correction factor to be ignored. The first assumption is justified by our desire for simplicity and by dealing here with responses within small imputation classes, results from these can then be summed for the entire sample. With these assumptions, $V_1(\bar{y}_r) = S_r^2/r$ where S_r^2 is the element variance of the y-variable in the population of respondents.

3. Selecting With or Without Replacement

As noted earlier, one type of "hot-deck" imputation scheme may be likened to the selection of an unrestricted sample of size m within the imputation class, and the random allocation of the sampled respondents' values to the nonrespondents. With the unrestricted sampling scheme for imputation, $V_2(\bar{y}_m) = s_r^2/m$, where $s_r^2 = \Sigma (y_{ri} - \bar{y}_r)^2/(r-1)$, and hence $E_1 V_2(\bar{y}_m) = S_r^2/m$ (we use lower case letters throughout for the conditional sample values, which become capitalized in their expected values). Thus for unrestricted sampling, and with $V_1(\bar{y}_r) = S_r^2/r$, and $\bar{m}^2 E_1 V_2(\bar{y}_m) = \bar{m}^2 S_r^2/r$,

$$I_u = \bar{m}(1 - \bar{m}) = P/(1 + P)^2$$

where $P = m/r$ is the ratio of nonrespondents to respondents, and $\bar{m} = P/(1 + P)$.

The maximum value of $I_u = 1/4$ occurs for its symmetrical curve when the nonresponse rate $\bar{m} = 1/2$ and $P = 1$. This additional imputation variance occurs for a "hot-deck" procedure with replacement from a randomly ordered list; this procedure may be criticized for the unnecessary multiple use of some respondents as donors.

The imputation variance may be reduced by selecting the sample of donors with SRS without replacement. When $r \geq m$ the additional variance becomes reduced to

$$I_o = \bar{m}(1-2\bar{m}) = P(1 - P)/(1 + P)^2$$

(Hansen et al., 1953, Vol. II, pp. 139-141; Kish, 1965, pp. 427-428).

The maximum increase of $I_o = 1/8$ occurs when $\bar{m} = 1/4$ and $P = 1/3$. Table 1 shows how much $I_o < I_u$, especially for larger values of $\bar{m}$. Though rare, it is possible for $\bar{m} > 0.5$, hence for $m > r$, so that a larger sample is needed than the size of the population from which it is being drawn. To cope with this problem, we generalize the without replacement sampling schemes as follows. Let $m = kr+t$, where k and t are non-negative integers and $t < r$; the case $k = 0$ covers the common situation when $r > m$. Then all respondents serve as donors of imputed values to nonrespondents on k occasions, with an epsem sample of t of them being selected without replacement to serve as donors on one more occasion. With such schemes, the mean of the imputed values can be expressed as

$$\bar{y}_m = (kr\bar{y}_r + t\bar{y}_t)/m$$

where $\bar{y}_t$ is the mean of the sample of t respondents selected for the additional donation, and

$$V_2(\bar{y}_m) = t^2 V_2(\bar{y}_t)/m^2 . \tag{3}$$

When the t respondents are selected by SRS,

$$E_1 V_2(\bar{y}_t) = (1 - t/r)S_r^2/t$$

so that in terms of $P' = t/r$,

$$I_o = P'(1 - P')/(k + 1 + P')^2, \tag{4}$$

in terms of $P = m/r = k + P'$,

$$I_o = (P - k)(k + 1 - P)/(1 + P)^2,$$

and in terms of $\bar{m} = m/n$,

$$I_o = [\bar{m}\ (1 + k) - k][(k + 1) - (k + 2)\bar{m}].$$

As Table 1 shows, the gains from using the SRS imputation scheme are particularly great for the rare cases when $k > 0$, i.e. when $\bar{m} > 0.5$.

Table 1. Proportionate increase in variance from using the unrestricted (I_u) and the SRS (I_o) imputation schemes for various nonresponse rates ($\bar{m}$)

$\bar{m}$	I_u	I_o
5%	0.0475	0.0450
15%	0.1275	0.1050
25%	0.1875	0.1250
35%	0.2275	0.1050
50%	0.2500	0.0000
65%	0.2275	0.0150
75%	0.1875	0.0000
85%	0.1275	0.0200

4. Stratified Sampling for Imputation

Sampling without replacement rather than with replacement is one way to reduce the imputation variance. Another way is to select a proportionate stratified sample of respondents to act as donors of values to the nonrespondents. In the usual survey sampling context the variable of interest is unknown and the strata are formed according to other characteristics assumed to be related to that variable. In the imputation situation, however, the respondents' values are known and can be employed in constructing the strata; in consequence stratification can be highly effective, reducing the imputation variance substantially.

We assume that the stratified sampling scheme is carried out without replacement so that, with $m = kr + t$, each respondent serves as a donor on k occasions and t respondents are selected by proportionate stratified sampling to serve on an additional occasion. Assuming for simplicity that r/t is an integer so that proportionality may be obtained strictly, $V_2(\bar{y}_m)$ for this scheme is given by (3) with

$$V_2(\bar{y}_t) = (1 - t/r)s^2_{rw}/t$$

where s^2_{rw} is the average within-stratum variance. The ratio of this conditional imputation variance to that pertaining when the SRS imputation scheme is used is thus $d = s^2_{rw}/s^2_r$. If respondents are stratified into several strata according to their y-values, this ratio can be small.

One simple scheme for stratifying respondents by their y-values is to divide them into s equal-sized strata, with the first stratum containing the r/s respondents with the largest y-values, the second stratum containing the r/s respondents with the largest y-values among the remainder, etc. (assuming for simplicity that r/s and t/s are integers). Then a SRS of t/s respondents is selected from each stratum to serve as donors on the additional occasion. This stratification by the variable of interest is closely related to the problems of grouping and matching, and results in these areas show that the ratio can be very small even for small values of s (see Aigner et al., 1975, the source of Table 2; Kish and Anderson, 1978; Anderson et al., 1980). To utilize the results from these other areas, d may be expressed as

$$d = \frac{(r-1)}{(s-1)}\frac{\Sigma\Sigma(y_{rhi} - \bar{y}_{rh})^2}{\Sigma\Sigma(y_{rhi} - \bar{y}_r)^2} = \left[\frac{(r-1)}{(r-s)}\right]\left[1 - \frac{v(\bar{y}_{rh})}{v(y_{rhi})}\right]$$

$$= [(r-1)/(r-s)](1-B) \qquad (5)$$

where y_{rhi} is the value of the y-variable for respondent i in stratum h ($i = 1,2,\ldots r/s$; $h = 1,2,\ldots s$), $\bar{y}_{rh} = s\Sigma y_{rhi}/r$ is the respondent mean in stratum h, $v(\bar{y}_{rh}) = \Sigma(\bar{y}_{rh} - \bar{y}_r)^2/s$, and $v(y_{rhi}) = \Sigma\Sigma(y_{rhi} - \bar{y}_r)^2/r$. The ratio $B = v(\bar{y}_{rh})/v(y_{rhi})$ has been termed the "relative explanatory power". The magnitude of B depends on the distribution of the y-variable, on the way the strata are formed and on the number of strata. Table 2 presents values of (1 - B) for the division of uniform, normal, exponential and beta (1/2, 1/2) distributions into equal-sized strata, with the number of strata ranging from 2 to 7.

Table 2. Values of (1 - B) for the division of four distributions into equal-sized strata

Number of strata (s)	Distribution: Uniform	Normal	Exponential	Beta (1/2,1/2)
2	0.25	0.36	0.52	0.19
3	0.11	0.21	0.35	0.09
4	0.06	0.14	0.26	0.05
5	0.04	0.10	0.21	0.03
6	0.03	0.08	0.18	0.02
7	0.02	0.06	0.15	0.02

Source: Aigner et al. (1975).

If r is large so that the factor (r-1)/(r-s) in (5) can be ignored, (1 - B) represents the multiplier to be applied to the SRS conditional imputation variance to reflect the effect of the stratified sampling scheme described above. As the results in Table 2 indicate, even with only two strata the multiplier is less than 0.5 for many distributions; and with five strata it is generally 0.1 or less. By applying the multiple of 0.1 to the proportionate increases in variance for the SRS imputation scheme, I_0, for various nonresponse rates given in Table 1, it can be seen that the imputation variance decreases to a negligible quantity. the maximum value of I_0 is 0.125 when the nonresponse rate is 25%, and this falls to 0.0125 when multiplied by 0.1. Providing r is large and five or more strata ($s \geq 5$) are used, the stratified imputation scheme can thus effectively eliminate the imputation variance. For dichotomous and polychotomous variables the case for stratification is even stronger because the imputation variance can be reduced toward zero to the extent that each stratum contains respondents from a single category.

The provisos that r is large and that $s \geq 5$ deserve comment since they may not hold within an imputation class. Imputation classes are formed by subdividing the total sample according to characteristics known for both respondents and nonrespondents, and often many characteristics are available for this purpose; as a result, numerous imputation classes may be formed, and many of them may be small in size.

If r is not large, the factor (r-1)/(r-s) in (5) will not be negligible. With r = 9 and s = 5, for instance, this factor is 2, and the 0.1 multiplier discussed above increases to 0.2. Even with this increase, the imputation variance for the stratified imputation scheme remains negligible. For smaller values of r, it is likely that fewer strata would be used (i.e., $s < 5$). It is, however, generally unwise to divide the sample into very small imputation classes because the resulting variability in the item nonresponse rates effectively creates large variation in the weights for different classes (this is the same point as applied with forming strata for post-stratification - see, for instance, Kish, 1965, pp. 90-92).

The maximum number of strata that can be used in an imputation class is s = t, the number of respondents needed to serve as donors on an additional occasion (m = kr + t). As Table 1 demonstrates, the imputation variance is negligible with the SRS scheme if k > 0, so that the significant benefits of the stratified scheme occur when k = 0, i.e. when m = t. In this case, the number of strata that can be formed in an imputation class is limited to be no greater than the number of nonrespondents in that class. It may be appropriate to combine an imputation class containing only one or two nonrespondents with an adjacent class in order to be able to employ several strata in the stratified imputation scheme, and hence reduce the imputation variance. Such a procedure, however, involves a subjective assessment of the trade-off between a reduction in imputation variance and an increase in nonresponse bias.

The preceding discussion has assumed for simplicity that r/s and t/s are integers, but this will not usually be so. In order to use the explicit stratification scheme described above, s could be chosen to be the highest common factor of r and t, but this would often result in a very small number of strata. A simple alternative is to use systematic sampling to obtain implicit stratification. The r respondents' y-values are listed in order of their sizes, and then a systematic sample of t respondents is selected from the list, using a procedure of random elimination, fractional intervals or a circular list if r/t is not an integer (see, for instance, Kish, 1965, p. 116). The systematic sampling scheme should also serve to make the imputation variance negligible providing m is not small.

5. Multiple Imputations: Two Techniques

In usual sampling situations a standard way to reduce variance is to increase sample size. In the imputation context the sample size is the number of nonrespondents m, but this number can be increased. The first technique, which we may designate as the fractional imputation technique (FIT), consists of dividing each of the nonrespondents' records into c parts, and assigning a weight of 1/c to each part. Then a sample of cm respondents can be selected to donate y-values to each of the parts. In this way each nonrespondent receives c imputed values. A second technique (described in detail in an appendix by Kish to a report by Kalton, 1981) consists of replicating all sampled elements c times, then selecting cm respondents to assign y-values to the cm nonrespondents so created; the sample of cm may be selected from the r respondents by the SRS scheme described in Section 2. The disadvantage of this second RRIP technique (RRIP, repeated replication imputation procedure) over the first FIT technique is the creation of a larger deck of cases. Its advantage is that it maintains a self-weighting deck of cases given that this exists initially. Both techniques reduce variances by decreasing the ratio of weights of imputed/nonimputed respondents from 2/1 to (c + 1)/c. As shown below the reductions are dramatic even for c = 2, and the variance tends to vanish for c = 3 or 4.

The use of multiple imputations has been advocated by Rubin (1978, 1979) for measuring the total variance of survey estimators including the imputation variance, for assessing the sensitivity of results to the imputation model, and for reducing the magnitude of the imputation variance. We are concerned here only with the last of these objectives, and will consider selection without replacement rather than the scheme with replacement proposed by Rubin, because the former yields lower variances. For multiple imputation without replacement m = kr + t becomes cm = ckr + ct, with the possibility that $ct \geq r$. Let ct = ar + u, with a and u integers and u < r, so that cm = (ck + a)r + u. Then (r-u) respondents donate values (ck + a) times to parts of nonrespondents and u respondents donate their values on (ck + a + 1) occasions.

An alternative, equivalent procedure with regard to estimating the population mean is to carry out single imputations for kr of the nonrespondents, and to use c multiple imputations only for the remaining t; with this procedure each respondent donates a value (k + a) times, and u respondents donate their values on an additional occasion. The advantage of this alternative is that it reduces the size of the file of records for analysis from [r (1 + ck) + ct] to [r (1 + k) + ct].

With either scheme the overall sample mean can be expressed as

$$\bar{y} = \{r\bar{y}_r[1 + k + (a/c)] + (u/c)\bar{y}_u\}/n$$

where $\bar{y}_u$ is the mean of the sample of u respondents. Hence the imputation variance with a SRS of u respondents is

$$E_1V_2(\bar{y}) = u(1 - u/r)S_r^2/c^2n^2$$

and the proportionate increase in variance from this imputation scheme is

$$I_m = ru(1 - u/r)/c^2n^2.$$

With n = r[1 + k + (a/c)] + (u/c) and letting P" = u/r, I_m becomes

$$I_m = P''(1 - P'')/[c(1 + k) + a + P'']^2.$$

For given g = c(1 + k) + a, the maximum value of I_m occurs when P" = g/(1 + 2g). The absolute maximum occurs when g is a minimum, i.e. when k = 0 and a = 0, and with c = 2 imputations per nonrespondent (with a single imputation per nonrespondent, c = 1, P" = P = 1/3, as noted above). In this case, P" = 2/5 (corresponding to P = 1/5 and $\bar{m}$ = 1/6) and I_m = 1/24 or 4.2%. When k = 0, a = 0 and c = 3, the maximum value of I_m is attained with P" = 3/7 (i.e. P = 1/7 and $\bar{m}$ = 1/8), when I_m = 1/48 or 2.1%.

In general, when a = 0, I_m can be expressed in terms of P' = t/r as

$$I_m = P'(1 - cP')/c(k + 1 + P')^2$$

$$= [\bar{m}(k + 1) - k][1 - ck - \bar{m}(1 + c - ck)]/c$$

Comparison of I_m with I_o for the SRS scheme in (4) shows that I_m is smaller than I_o by the factor $(1/c)$ and by the factor $(1 - cP')/(1 - P')$. The first factor comes about because of the increase in the sample size from m to cm and the second factor because of the decrease in the finite population correction term.

The reduction in imputation variance through the use of multiple imputations is most important in the range $0\% < \bar{m} < 50\%$, since this is where the imputation variance is sizeable with the SRS scheme. In this range $k = 0$, and if $a = 0$, I_m reduces to

$$I_m = \bar{m}[1 - \bar{m}(1 + c)]/c.$$

Table 3 compares the values of I_o and I_m for $c = 2$ in this range. It shows that the use of only two imputations per nonrespondent markedly reduces the imputation variance. The use of three or four imputations per nonrespondent makes it practically vanish.

Table 3. Proportionate increase in variance from using the SRS imputation schemes with $c = 1$ (I_o) and $c = 2$ (I_m) imputed values for each nonrespondent for various nonresponse rates ($\bar{m}$).

$\bar{m}$	I_o	I_m
5%	0.04500	0.02125
10%	0.08000	0.03500
15%	0.10500	0.03125
20%	0.12000	0.04000
25%	0.12500	0.03125
30%	0.12000	0.01500
35%	0.10500	0.00750
40%	0.08000	0.02000
45%	0.04500	0.01750

6. Discussion

The results in the preceding sections have demonstrated that substantial reductions in imputation variance can be achieved by selecting donors from the respondents by simple random sampling without replacement, by stratified sampling, and by the use of multiple imputations as compared with unrestricted sampling. The commonly-used "hot-deck" imputation procedure most closely resembles the unrestricted sampling procedure, and it appears that the use of the alternative procedures would yield considerable improvements on it. It should, however, be noted that in practice the order of the data file for the "hot deck" is not a random one, and the order may produce some additional "closeness" of match between respondents and nonrespondents. However this "closeness" may well be exaggerated for imputation classes which denote small subclasses in the sample. On the other hand, imputation variance may often have been neglected.

It should also be pointed out that the "hot deck" procedure can be carried out very simply with a single computer pass of the survey records, whereas the alternative procedures need more computer processing. Sampling without replacement schemes require the survey records first to be separated into imputation classes, and within classes into records with responses to the item in question and records without such responses. The stratification scheme requires that the respondents' records then be sorted into strata according to their y-values, or listed in order of their y-values for systematic sampling. While these requirements make the procedures more expensive in computer time, they can nevertheless be carried out at reasonable cost with efficient programming. Coder (1978) and Welniak and Coder (1980), for instance, describe a complex imputation scheme used with the income supplement to the March CPS which is based on a sorting and matching operation for respondents and nonrespondents.

It should be further noted that for simplicity we have discussed imputation in terms of only a single item with missing data, whereas in practice survey records often contain many missing values. When the survey objectives include the estimation of the interrelationships between a set of items, it is useful to replace all of a record's missing values in the set by the responses of a single donor. The use of joint imputation also avoids inconsistencies among the imputed values. No problems arise in incorporating joint imputation into the SRS and multiple imputation schemes, but it is less easily handled with the stratified scheme. For instance, if the donors are selected by systematic sampling from the list of respondents ordered by their values on one item, the reductions in imputation variance from this implicit stratification for the other items depend on the strengths of the correlations between the one item and the other items; sizeable correlations are needed if the reductions are to be appreciable. The items chosen for joint imputation are in fact often closely related, but this need not always be so.

A cost in using a multiple imputation scheme is that the data file has to be enlarged from r + m to r + cm (or at least to r + m + (c - 1)t) records with the FIT technique and to c(r + m) records with the RRIP technique. The enlarged data file has then to be used for all the survey analyses.

The stratified and multiple imputation schemes have been discussed separately as alternative methods for reducing imputation variance, but they can also be combined. As described in Section 4, the u respondents selected in the multiple imputation scheme to serve as donors on the additional occasion were drawn by SRS but they could equally have been drawn by stratified or systematic sampling: in this way, the gains from stratification and multiple imputation would be combined. Another possibility would be to employ the stratified imputation scheme in imputation classes in which there are sufficient numbers of nonrespondents to enable several strata to be formed (say 4 or more) and to use multiple imputations (perhaps with stratification) in other strata.

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