APPLYING MASS IMPUTATION USING THE SCHOOLS AND STAFFING SURVEY DATA

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1. Introduction

During the past few years the authors have been trying to find a methodology which produces a set of survey weights for which the estimates of number of schools, students and teachers agree for both a sample survey and its frame. The frame estimates are produced for the same time period as the survey collection. Of course, the "control" is only achieved for a specified set of cells.

If there were only one estimate, say number of schools, then a simple raking procedure would do the job. However, we require the agreement of three independent estimates simultaneously. Raking does not converge for this problem.

Scheuren and Kaufman (1996) found a solution using a generalized least squares methodology (GLS). Using a multivariate ratio adjustment first, weights less than 1 for the most part become minimal; and the implementation become manageable. The problem with our "solution" is that for cells not controlled for, the original weights quite often produce closer agreement than the GLS weights. In the 1996 paper, it was proposed that a mass imputation procedure (Kovar and Whitridge 1995) might provide better results.

Mass imputation is where the survey respondents are used as donors to impute back to the entire frame. If the survey respondent data were mass imputed to the frame for all data elements except the schools, students and teacher elements then the desired consistency would be achieved for all estimation cells. All weights would equal 1 and the survey estimates for schools, students and teachers would equal the frame total.

The principal problem with this version of mass imputation is the difficulty in variance estimation for survey variables other than school, student and teachers. Since values are assigned to the entire frame, standard variance procedures produce a zero variance. A variance procedure that measures the imputation variance is required to compute the mass imputation variance estimates.

Shao and Sitter (1996) proposed a methodology for measuring the imputation variance. It works for general estimates coming from any sample design and imputation methodology. The methodology calls for generating bootstrap samples of both respondents and nonrespondents. The original imputation procedure is applied to each bootstrap sample; and the distribution of bootstrap estimates is relied on for inference.

This paper investigates the magnitude of the precision gains that we thought mass imputation promised. Additionally, a variance estimator for the mass imputation, motivated by the Shao and Sitter methodology, is developed. (One potential problem, for example, with the Shao and Sitter methodology is the assumption that probabilities of being a nonrespondent are equal within an imputation cell. With mass imputation, this need not necessarily be true.)

The precision gains of mass imputation and its proposed variance estimator are tested through a simulation study. Frame variables are used, so that true values for all sample imputed estimates are known. The "respondents" or donors are determined using a single stage probability proportionate to size sample design, similar to the Schools and Staffing Survey. Given these respondents:

(1) A mass imputation is performed and compared with the standard Horvitz-Thompson estimator.

(2) Further, an estimate of the true mean square error (MSE) of the mass imputation estimate is compared to the Horvitz-Thompson variance.

(3) Additionally, the proposed mass imputation variance is computed and compared to an estimate of its true variance. Since all sample estimates can be obtained exactly, estimates of the true variance are computed using the simple variance of the selected simulation sample estimates.

(4) Finally, the case when nonrespondents are selected completely at random will be investigated by simulating a sample design following this assumption.

2. NCES Applications for Mass Imputation

The motivating application for mass imputation is the GLS problem described in the introduction. However, two other applications are possible. For example, NCES uses indirect estimation procedures to produce state private school enrollment figures. The estimation procedure applies an adjustment factor to each known private school. The adjustment reflects results from a survey that measures the number of schools missing from our lists. Since this is a mass imputation procedure, the results of this paper can be useful in the variance estimation of these state estimates.

Another potential application of mass imputation is in the Center's data warehousing project. Here, the object is to link past and current Center surveys across program areas. If sample surveys are mass imputed to their frame, then the linkage problem is reduced to linking the frames, eliminating the need to link all the sample surveys. Again, the variance estimator proposed here might be useful.

3. Imputations

3.1 Nearest Neighbor Imputation. -- The nearest neighbor imputations used in this paper are done within imputation cells, after the schools have been sorted by the number of students per school. The imputation cells are state/school level/urbanicity. There are three school levels - elementary, secondary and combined; also three levels of urbanicity - central city, urban fringe/large town and rural/small town. After the file is sorted, it is accessed sequentially using the nearest responding school as the donor for a nonresponding school. For a particular unit i, we represent the imputed value for variable y_i by $y_{i\bullet}$.

The imputation described above is used two ways with different file sortings before the imputations are determined. The first imputation sorts the file in ascending order within imputation cell. This will be referred to as ascending imputation. The second imputation is done by determining the imputations in ascending, as well as descending order. Each time an imputation is required, a random 50/50 selection is used to determine which imputation is used in the estimate.

3.2 Mass Imputation. -- In mass imputation the sample weights associated with a probability sample s are ignored. Instead, it is assumed that the entire frame is in the sample, but the only units that respond are the units in s. Estimates are produced by assigning all units on the frame a weight of 1 and using the units in s as the donors to impute all the other frame units. The nearest neighbor imputation, described above, was used in the mass imputation process. After the imputation, estimates were computed as though the entire frame responded. If the imputation process is "good," then there may be some efficiency gains, compared to the usual Horvitz-Thompson estimator.

4. Sample Selection (Mass Imputation Donors)

Two sample designs will be used. The main design studied employed the square root of the number of teachers in a school as a PPS measure of size; the second (subsidiary) design selected units with equal probability within an imputation cell. The first is used to test the mass imputation procedures under the SASS sample design, while the second is used for comparison to verify the importance of the missing completely at random assumption.

4.1 The Schools and Staffing Sample Design. -- The Schools and Staffing Survey (SASS) is a stratified probability proportionate to size (PPS) sample of elementary, secondary and combined schools. The selection is done systematically using the square root of the number of teachers per school as the measure of size. State-by-school level cells define the stratification. Before systematic selection, schools are sorted to provide a good geographic distribution. Sample allocations are designed to provide reliable state estimates. In this simulation study, four small States were studied. The sample state sizes ranged from 72 to 196 schools. The sampling rates ranged from 14 to 42 percent of each state's school population.

In order to eliminate the SASS design effects from systematic sampling and high sampling rates, the simulation split each state/school level stratum into a number of substrata (h) so that exactly two schools are selected within each substratum **with replacement**. The original SASS sample sizes by state were, however, maintained.

4.2 The Equal Probability Sample Design. -- The Shao - Sitter variance methodology assumes that nonrespondents are missing completely at random. To test the importance of this assumption in the SASS setting, the sample selection procedure described above was modified to select each school in a stratum with equal probability. Within each state, the sample sizes again remained the same, but the allocation and stratification boundaries were altered to achieve the desired equal selection probabilities. Again, two units will be selected within each stratum **with replacement**.

5. Mass Imputation Bootstrap Variances

To generate the bootstrap variance estimator for an estimate θ, the following is done:

(1) A bootstrap sample s^* is generated by selecting 2 units from s within each of the h stratum. The selection is done with equal probability and with replacement.

(2) Then s^* is sorted by the imputation cell and one bootstrap unit is randomly selected within each imputation cell and eliminated from s^*. This is done in an attempt to produce a more unbiased variance estimate. The Shao - Sitter procedure does this by selecting n-1 units within each stratum. In the Shao and Sitter setting, this is appropriate since variability is introduced through the sampling mechanism. In the mass imputation setting, there is only an imputation variance. Therefore, the appropriate place to reduce the sample size seemed to be where the imputation process begins – the imputation cells. To verify that the imputation cell

is the appropriate place to reduce the bootstrap sample size by one, a simulation was done, reducing the sample size in the stratum controlling the donor selection. (See Table 4)

(3) The bootstrap mass imputation is generated by doing the mass imputation procedure on the original frame using the units determined in step 2 as donors.

(4) Using the results from step 3, compute the bootstrap estimate θ^* the same way θ is calculated.

(5) Repeat steps (1) to (4) B times, producing bootstrap estimates θ_j^*, j equaling 1 to B.

(6) The simple variance of the θ_j^* is our bootstrap variance estimate ($V^*(\theta)$).

6. Simulations

There were 2,000 simulations performed for each sample design described above. Mass imputations and bootstrap variances are computed for each simulation. The estimate and analysis statistics used in the simulation are described below.

6.1 Estimates. -- Four mass imputation estimates per state are computed:

$$\hat{y}_{Me1} = \sum_{k\in N} S_k p_{ke1}; \hat{y}_{Me2} = \sum_{k\in N} S_k p_{ke2};$$

$$\hat{y}_{Mm} = \sum_{k\in N} S_k p_{km}; \text{and } \hat{y}_{Mh} = \sum_{k\in N} S_k p_{kh}.$$

S_k is the known number of students in school k

p_{ke1} : student proportion in school k grades pre-kindergarten to 3

p_{ke2} : student proportion in k grades 4 to 6

p_{km} : student proportion in k grades 7 to 9

p_{kh} : student proportion in k grades 10 to 12

It is assumed that S_k is known for all k and that only the p's require collection. Therefore, when k is not selected to be a responding unit, a nearest neighbor donor's p will be applied to S_k.

Additionally, four Horvitz-Thompson estimates are computed within each state:

$$\hat{y}_{e1} = \sum_{k\in s} w_k S_k p_{ke1}; \hat{y}_{e2} = \sum_{k\in s} w_k S_k p_{ke2};$$

$$\hat{y}_{m} = \sum_{k\in s} w_k S_k p_{km}; \text{and } \hat{y}_{h} = \sum_{k\in s} w_k S_k p_{kh}.$$

where: w_k is the inverse of the selection probability and s is the set of all selected schools.

6.2 Simulated Variance and Bias Estimates. -- The two variance estimates computed within each sample and averaged across samples are:

$$V^*(\hat{y}_\bullet) = 1/B\sum_{j=1}^{B}(\hat{y}^*_{\bullet j} - \bar{y}^*_\bullet)^2$$

$\hat{y}_\bullet$: mass imputation estimates described above,

$\hat{y}^*_{\bullet j}$: a bootstrap estimate of $\hat{y}_\bullet$,

$\bar{y}^*_\bullet$: the average of the bootstrap estimates $\hat{y}^*_{\bullet j}$.

Estimates of the true variance of the mass imputation estimate ($\hat{y}_\bullet$) and the Horvitz-Thompson estimate ($\hat{y}$) are provided below:

$$V_T(\hat{y}_\bullet) = 1/n\sum_{s=1}^{n}(\hat{y}_{\bullet s} - \bar{y}_{\bullet s})^2$$

$\hat{y}_{\bullet s}$ and $\bar{y}_{\bullet s}$ are the value of $\hat{y}_\bullet$ for the s^{th} simulation and the average of the $\hat{y}_{\bullet s}$, respectively.

$$V_T(\hat{y}) = 1/n\sum_{s=1}^{n}(\hat{y}_s - \bar{y}_s)^2$$

$\hat{y}$: Horvitz-Thompson estimate,

$\hat{y}_s$: s^{th} Horvitz-Thompson estimate,

$\bar{y}_s$: average of the Horvitz-Thompson estimates.

The bias of the mass imputation estimate ($\hat{y}_\bullet$) is estimated by:

Bias($\hat{y}_\bullet$)= $\bar{y}_{\bullet s} - \bar{y}_s$

7. Analysis Statistics from Simulations

Four tables are provided at the end of this paper which provide summaries of our simulation results. Three key analytic statistics have been used:

(1)To evaluate the imputation methodology, the relative bias of the estimated standard error (RBS) is computed.

$$RBS = \left(\sqrt{\hat{V}(\hat{y}_\bullet)} - \sqrt{V_T(\hat{y}_\bullet)}\right)/\sqrt{V_T(\hat{y}_\bullet)}$$

(2) The relative precision of the mass imputation estimate (RPS) is given by:

$$RPS = \sqrt{\left(V_T(\hat{y}_\bullet) + \text{Bias}^2(\hat{y}_\bullet)\right)}/\sqrt{V_T(\hat{y})}$$

(3) The relative bias of the mass imputation estimate (RBE)

$$RBE = (\bar{y}_{\bullet s} - \bar{y}_s)/\bar{y}_s.$$

7.1 Table 1 Overall Comparisons. -- Table 1 displays how mass imputation might work in the SASS setting using ascending imputations. The answer to the question of whether this approach is satisfactory is "no." The precision of mass imputation relative to the Horvitz-Thompson clearly gives the Horvitz-Thompson estimator the advantage. The mass imputation estimator only once has a large efficiency gain over Horvitz-Thompson (18.4 percent). Seven times there was not much difference between the two estimation methods. In these cases, the gains ranged from -11.5 to +12.4 percent. On the other hand, there were eight times when mass imputation had a big precision loss. In these latter cases, the lost was between -15.3 and -61.1 percent. Overall, mass imputations perform poorly for these estimates in the states tested.

7.2 Table 1 Standard Error Comparisons. -- Table 1 also demonstrates with ascending imputations, through the relative bias of the standard error (RBS) values shown there, that our variance procedure underestimates the standard error. Most of the time the absolute bias is less than 10 percent. The reason for the underestimate may be the way the bootstrap sample sizes were reduced by one. Some theoretical work may be needed to provide an unbiased estimator. Another possible reason (See Table 2 below), is the inappropriateness of the completely missing at random assumption for the nonrespondents.

7.3 Table 2 Standard Error Comparisons. -- The purpose of table 2 is to investigate (using ascending imputations) the robustness of the missing completely at random assumption of the variance procedure. Comparing the relative biases of the standard error in tables 1 and 2 shows that the standard errors are reasonably close to the true values, but still consistent underestimate. When the missing completely at random assumption is violated (table 1), there are more large underestimates than when the assumption is not violated. This indicates the missing completely at random assumption is not critical in this setting, but cannot be completely ignored.

7.4 Other Points from Table 2. -- Table 2 also demonstrates another point. Since the selection and allocation are designed to produce an equal probability sample, one might expect the Horvitz-Thompson estimator to be inefficient estimating total numbers of students. That being the case, the mass imputation might compensate for the deficiencies in the sample design and be more efficient then the Horvitz-Thompson estimator. This does not appear to be true. The mass imputation does much worse than the Horvitz-Thompson estimator five times. In those cases, the loss of precision ranged from -21.2 to -43.1 percent. The mass imputation has large precision gains five times. The gains ranged from +19.4 to +33.4 percent. However, it should be noted that mass imputation with the equal probability design performed better than the unequal probability design. Therefore, there is some truth to the assertion made at the beginning of this paragraph.

7.5 Table 3 Ascending and Descending Imputation. -The purpose of table 3 is to determine whether mass imputation might work in the SASS setting when both ascending and descending imputations are used. The answer to this question is still "no." Twice the mass imputation was much better than Horvitz-Thompson. In these cases, the gains were +23.2 and +27.2 percent. Eleven times there was not much difference between the two estimation methods. In these cases, the gains ranged from –14 to +11.2 percent. Three times, mass imputation had a big precision loss between -17.1 to -21.9 percent.

Still, as might be expected intuitively, using the ascending/descending imputation works much better than just ascending imputation. This is seen by comparing Tables 1 and 3. Using the ascending imputation, mass imputation is reasonably close or better than Horvitz-Thompson eight times, while the ascending/descending is reasonably close or better thirteen times. One reason for this is that the ascending/descending imputation is generally less biased. Since both imputation methodologies have small biases, this is not the main reason for the difference.

The main reason for the difference is a smaller variance. Now there are two ways to reduce this variance: (1) reduce the variability of the donor enrollment counts or (2) reduce the variability of the weights. Since donor enrollment counts are the same for both imputation methodologies, the reduction in variance is coming entirely from reducing the variability of the weights. Since the ascending/descending mass imputation imputes values from both sides of the missing data at an expected 1 to 1 rate, the implicit weight for this processes will be (more or less) the moving average of the individual ascending and descending imputation weights. Since the units are sorted by size, the weights should be increasing as you go down the file. Therefore, the moving average of the weights should be less variable than the individual weights.

7.6 Table 4 On Bootstrap Bias Issues. -- Table 4 displays what happens when reducing the bootstrap sample sizes by one at the sampling stratum level, rather than at the imputation cell level as earlier. As can be seen in the relative bias of the standard error from table 4, the standard errors are overestimated by +24 to +48 percent. This shows that reducing the bootstrap sample size at the imputation cell level, although a slight underestimate, is better than doing it at the sample stratum level. Again, some work on the theory would seem to be needed here.

8.0 Conclusions And Areas For Future Study

8.1 Some Basic Conclusions. -- A lot was learned from the simulation work discussed here:

(1) We remain convinced, for example, of appeal of being able to make greater use of the frame variables to improve estimation; however, we now have a much greater appreciation of the practical

difficulties in an actual implementation of such a procedure.:

(2) Broadly speaking, for the states and variables used in the present analysis, the bias in the mass imputation estimator, no matter how conducted, is relatively small. This suggests that any of the nearest neighbor imputation variants employed here would be sufficient for a mass imputation process.

(3) However, while at times the mass imputation estimator did outperform the Horvitz-Thompson estimator, it just never performed better overall.

(4) Of the two methods of imputation employed, the ascending/descending method was clearly superior to just using the ascending method alone.

(5) As our work on the robustness of the "missing at random" assumption demonstrated, the sample design and the imputation procedure cannot be treated independently.

(6)The variance estimation procedure proposed in this paper seems to work reasonably well. Most of the time, it underestimates the variance slightly. Occasionally, though, the variance is greatly underestimated, especially when the selection probabilities within imputation cells are unequal.

(7) The proposed variance procedure does not appear to be unbiased, although some ad hoc adjustments seem clearly better than others (e.g., adjusting at the imputation cell rather than stratum level).

8.2 Some Next Steps and Second Thoughts. -- Without question we were disappointed with the performance of mass imputation. While not a failure, so far it has not delivered on our expectations. Some conjectures about why:

(1) One possible reason is that, even though the imputation took school size into account, there were not enough large schools selected in the equal probability design to measure the large school's distribution appropriately. As noted already, users of mass imputation must take the sample design into account when determining an appropriate imputation.

(2) Another possibility is that a better imputation procedure needs to be used. Fixing either of these possibilities requires designers very knowledgeable about the data being imputed. Clearly, just using a relatively efficient general imputation procedure, like nearest neighbor, does not guarantee good performance of the mass imputation estimator.

(3) In doing the imputations, no control was introduced on the number of times a donor case was used. If done, this, all by itself, might have improved our results dramatically. We conjecture that the cases where extremely poor results were obtained would have been lessened.

(4) Theoretical work on nearest neighbor imputation, given at these meetings, also is a place to look for ideas for improvements (Chen and Shao 1997). In addition, theoretical work seems required to find an unbiased variance methodology. Even so, given the general difficulty of variance estimation for indirect estimates, the variance procedure described here may be applicable to the indirect estimation problem stated in section 2. We are less sure, by the way, about the application of mass imputation to NCES's data warehousing work.

(5) If the ascending/descending mass imputation is used when the donors are selected with equal probability, then the mass imputation may well outperform Horvitz-Thompson. However, there was not the time to do this simulation for the present paper.

(7) While we started off our work determined to better the GLS procedures studied earlier, no direct comparison was made here with a comparable GLS estimator. We conjecture that mass imputation at best may be not much better than a "wash' when imputing based on a single variable; but that as the dimensionality of the information used from the frame grows, mass imputation may yet show it value.

Table 1 -- Relative Precision (RPS), Bias (RBS) of the Mass Imputation Standard Error and Relative Bias (RBE) of the Estimator using SASS Sample Design and Ascending Imputations

State	Est.	Standard Error		Estimate
		Relative Precision	Relative Bias	Relative Bias
2	$\hat{y}_{Me1}$	100.2	-5.7	0.1
	$\hat{y}_{Me2}$	89.7	-8.8	-0.2
	$\hat{y}_{Mm}$	112.4	8.4	-2.0
	$\hat{y}_{Ms}$	88.5	5.5	2.7
9	$\hat{y}_{Me1}$	136.2	-17.6	-3.3
	$\hat{y}_{Me2}$	126.0	-18.0	-0.1
	$\hat{y}_{Mm}$	137.3	-16.5	3.0
	$\hat{y}_{Ms}$	81.4	-6.9	1.9
10	$\hat{y}_{Me1}$	132.2	-3.3	-3.3
	$\hat{y}_{Me2}$	115.3	-3.8	3.8
	$\hat{y}_{Mm}$	118.9	3.6	0.9
	$\hat{y}_{Ms}$	99.4	11.6	-.04
24	$\hat{y}_{Me1}$	161.1	-9.7	-4.5
	$\hat{y}_{Me2}$	108.0	-19.3	-0.5
	$\hat{y}_{Mm}$	156.1	-9.4	5.3
	$\hat{y}_{Ms}$	104.4	-10.8	1.3

Table 2 -- Relative Precision (RPS), Bias (RBS) of the Mass Imputation Standard Error and Relative Bias (RBE) of the Estimator with Equal Probability Selection of Donors and Ascending Imputations

State	Est.	Standard Error		Estimate
		Relative Precision	Relative Bias	Relative Bias
2	$\hat{y}_{Me1}$	92.3	-10.6	0.1
	$\hat{y}_{Me2}$	72.9	-10.0	0.5
	$\hat{y}_{Mm}$	110.7	-5.3	1.5
	$\hat{y}_{Ms}$	80.6	-2.2	-2.9
9	$\hat{y}_{Me1}$	123.2	-11.7	-0.8
	$\hat{y}_{Me2}$	106.0	-16.6	0.0
	$\hat{y}_{Mm}$	112.3	-12.6	-0.2
	$\hat{y}_{Ms}$	66.6	-2.9	1.6
10	$\hat{y}_{Me1}$	133.2	-0.1	-1.5
	$\hat{y}_{Me2}$	98.5	0.4	2.1
	$\hat{y}_{Mm}$	121.2	-2.9	2.0
	$\hat{y}_{Ms}$	96.6	12.4	-3.0
24	$\hat{y}_{Me1}$	143.1	-13.3	-2.4
	$\hat{y}_{Me2}$	80.4	-14.1	-0.3
	$\hat{y}_{Mm}$	128.7	-13.2	3.1
	$\hat{y}_{Ms}$	68.6	-8.0	0.8

Table 3 -- Relative Precision (RPS), Bias (RBS) of the Mass Imputation Standard Error and Relative Bias (RBE) of the Estimator using SASS Sample Design and Ascending and Descending Imputations

State	Est.	Standard Error		Estimate
		Relative Precision	Relative Bias	Relative Bias
2	$\hat{y}_{Me1}$	92.6	-1.0	0.9
	$\hat{y}_{Me2}$	88.8	-6.0	-0.3
	$\hat{y}_{Mm}$	103.2	14.7	-1.8
	$\hat{y}_{Ms}$	72.8	21.9	0.3
9	$\hat{y}_{Me1}$	109.9	-17.6	-1.4
	$\hat{y}_{Me2}$	110.5	-18.3	0.2
	$\hat{y}_{Mm}$	109.1	-15.0	1.0
	$\hat{y}_{Ms}$	76.8	-1.9	1.1
10	$\hat{y}_{Me1}$	121.9	0.5	-0.1
	$\hat{y}_{Me2}$	108.2	1.9	0.5
	$\hat{y}_{Mm}$	114.0	3.1	0.0
	$\hat{y}_{Ms}$	94.4	15.4	-0.4
24	$\hat{y}_{Me1}$	120.3	-13.7	-1.4
	$\hat{y}_{Me2}$	92.1	-20.9	-0.2
	$\hat{y}_{Mm}$	117.1	-13.4	1.7
	$\hat{y}_{Ms}$	93.9	-4.8	0.3

Table 4 -- Relative Bias (RBS) of the Mass Imputation Standard Error, Adjusting the Bootstrap Sample Size at the Donor Selection Stratum Level using Ascending Imputations

State	Est.	Relative Bias	State	Est.	Relative Bias	State	Est.	Relative Bias	State	Est.	Relative Bias
2	$\hat{y}_{Me1}$	36.4	9	$\hat{y}_{Me1}$	24.3	10	$\hat{y}_{Me1}$	43.8	24	$\hat{y}_{Me1}$	28.9
	$\hat{y}_{Me2}$	30.6		$\hat{y}_{Me2}$	24.6		$\hat{y}_{Me2}$	42.6		$\hat{y}_{Me2}$	24.1
	$\hat{y}_{Mm}$	30.5		$\hat{y}_{Mm}$	25.2		$\hat{y}_{Mm}$	32.2		$\hat{y}_{Mm}$	29.6
	$\hat{y}_{Ms}$	30.5		$\hat{y}_{Ms}$	46.0		$\hat{y}_{Ms}$	47.6		$\hat{y}_{Ms}$	27.5

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