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IMPUTATION VS REWEIGHTING FOR TOTAL NONRESPONSE IN A BUSINESS SURVEY

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ABSTRACT

The two strategies for handling total nonresponse in a repeated business survey are discussed and their use is illustrated with the Quarterly Motor Carriers of Freight Survey of Statistics Canada. Estimators that use imputed data, estimators based on reweighting and estimators that use both reweighting and auxiliary variables are compared.

RÉSUMÉ

Deux stratégies permettant de traiter la non-réponse totale pour une enquête-entreprises périodique seront examinées et illustrées à l'aide de l'enquête trimestrielle sur les transporteurs routiers de marchandises de Statistique Canada. On comparera entre eux des estimateurs construits à partir de données imputées, des estimateurs faisant intervenir une repondération, et des estimateurs utilisant à la fois une forme de pondération et des variables auxiliaires.

1. INTRODUCTION

Total nonresponse, also referred to as unit nonresponse, happens when no data is collected for some units that were selected for a survey. This could be caused by a number of reasons. For example no data will be available for units that could not be reached during the collection period because their contact information was incorrect or out-of-date or because the respondent was absent during the collection period. Another example is units that are reached, however either cannot or do not want to provide any of the information required by the survey. So the only information available for these units will be information known prior to the data collection that is available for all units on the survey frame as well as the reason for not providing the survey data.

The amount of total nonresponse varies from survey to survey depending on the quality of the frame contact information, the method of data collection, the subject matter of the survey, length and complexity of the questionnaire and the amount of burden it presents to the respondents, the population being surveyed and its willingness to cooperate, the amount of follow-up and many other factors. The challenge for the survey-taking organization is to keep the response rates as high as possible while operating within budget constraints and then produce good-quality estimates based on the respondents' data only.

In this paper we consider handling nonresponse at the estimation stage. We assume that the collection period for a survey is over and the amount of total nonresponse cannot be decreased. Two available solutions - imputation and reweighting - are discussed in Section 2. Their advantages and disadvantages in the case of a repeated business survey are assessed in Section 3. Finally, an example of a comparison between these two methods using data from the Statistics Canada Quarterly Motor Carriers of Freight Survey is presented in Section 4.

2. SOLUTIONS FOR TOTAL NONRESPONSE AT THE ESTIMATION STAGE

2.1 Framework

Let U denote the finite survey population of N units for which information is required and F be the frame that provides access to the survey population units. The frame is a list of sampling units that contains contact information such as name, address, phone number, *etc.* and usually also additional information for every unit. The additional information could, for example, be a measure of size for every unit or information on the unit's membership in a certain subpopulation (*e.g.*, certain industry). This additional information is usually used to improve the efficiency of the survey design and of the estimates. A probability sample s of n sampling units is selected from the frame F using a sampling design p that gives every unit on F a nonzero probability of selection $\Pr(k \in s) = \pi_k$. This probability is often referred to as the *inclusion probability of unit k*. The inverse of the inclusion probability, $w_k = 1/\pi_k$, is referred to as the *design weight of unit k* and it is used to expand the values of the kth unit in the sample in order to produce estimates for the entire survey universe U.

At the end of the survey collection period, the sample is composed of two sets:

$$s = s_R \cup s_N , \tag{1}$$

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where s_R denotes the set of respondents and s_N denotes the set of nonrespondents. Suppose that the surveyor is interested in the total of the variable y, $Y = \Sigma_U y_k$, where Σ_U denotes the summation over all N population units. If the variable y was observed for all units in s then an estimator $\hat{Y}$ based on the entire s could be used:

$$\hat{Y} = \Sigma_s \; a_k y_k \, , \tag{2}$$

where a_k is the weight of the unit k in s. If the simple expansion estimator (also referred to as the Horvitz-Thompson or π estimator) is used, then $a_k = w_k$. If a more complex estimator (*e.g.*, regression or post-stratified estimator) is used, then $a_k = g_k \; w_k$, where g_k is some sample dependent weight that uses auxiliary data. The properties of $\hat{Y}$, design bias and variance, could be derived using the sampling design p as follows:

$$B\,(\hat{Y}) = E_p\,(\hat{Y}) - Y, \tag{3}$$

$$V\,(\hat{Y}) = E_p[\,\hat{Y} - E_p\,(\hat{Y})\,]^2 \, , \tag{4}$$

where E_p denotes expectation calculated using the sampling distribution of $\hat{Y}$ under the design p. Because the values of y are not available for all units in s_N a different estimator must be used to estimate Y.

2.2 Imputation

One approach to produce estimates when data are missing is to replace the missing values with some artificial but plausible values. This approach is called *imputation* and is often used to impute missing data for partial respondents (partial respondents are sampled units for which only some requested data was collected) or to replace incorrect and inconsistent values for respondents. However, in business surveys, imputation is also sometimes used to create artificial data for the entire set s_N before estimation. In such a case, the estimator of Y is

$$\hat{Y}_{IMP} = \sum_{s_R} a_k y_k + \sum_{s_N} a_k y_{k,\,IMP}, \tag{5}$$

where $\sum_{s_R}$ is the summation over all units in the respondent set, $\sum_{s_N}$ is the summation over all units in the nonrespondent set, and $y_{k,\,IMP}$ is the imputed value of the variable y for the unit k in the set s_N.

What are the properties of $\hat{Y}_{IMP}$ and how do they compare with the properties of $\hat{Y}$? In general, $\hat{Y}_{IMP}$ is biased, *i.e.*, $B\;(\hat{Y}_{IMP})$ is different from zero unless the imputation procedure reproduces the true value y_k for every unit k in s_N. Lee, Rancourt and Särndal (1994) found that the bias can be very severe when the response mechanism is confounded. In their study, *confounded response mechanism* given s depends on the y-values in s. On the other hand, their Monte Carlo simulations showed that the bias can be tolerable when the nonresponse occurs at random.

For the comparison of variances $V\,(\hat{Y})$ and $V\,(\hat{Y}_{IMP})$ the result obtained by Särndal (1990) can be used. The total error of $\hat{Y}_{IMP}$ can be decomposed as

$$\hat{Y}_{IMP} - Y = (\hat{Y} - Y) + (\hat{Y}_{IMP} - \hat{Y}) = \text{sampling error} + \text{imputation error}, \tag{6}$$

and the total variance can be written as

$$V\,(\hat{Y}_{IMP}) = V_{SAM} + V_{IMP} + V_{MIX}\,, \tag{7}$$

where V_{SAM} is the sampling variance, V_{IMP} is the variance due to imputation, and V_{MIX} is a covariance term between V_{SAM} and V_{IMP}. Särndal derived the variance terms using a *model assisted* approach with three different probability distributions - sampling distribution, imputation model and response mechanism. Past simulation studies showed that the last term, V_{MIX}, is often negligible and can usually be ignored. The imputation variance V_{IMP} is zero only if $y_{k,\,IMP} = y_k$ for every unit k in the set s_N and therefore we can conclude that $V\,(\hat{Y}_{IMP}) > V\,(\hat{Y})$ in every practical situation.

To estimate $V\,(\hat{Y}_{IMP})$ one needs to estimate the two components, sampling variance and the variance due to imputation. When the standard design-based variance estimate is used with imputed data treated as observed data, the variance of $\hat{Y}_{IMP}$ is underestimated. This approach is sometimes referred to as the "naive approach" and therefore we will denote such an estimate by v_{NAIVE} . The naive variance estimate measures the sampling variance component only but often underestimates V_{SAM} because many imputation methods produce data that are less variable than the true values would be. The amount of underestimation by v_{NAIVE} was assessed for different imputation methods and nonresponse rates in a number of Monte Carlo studies, for example by Kovar and Chen (1994) and Lee, Rancourt and Särndal (1994). Currently methods to produce a correct estimate of $V\,(\hat{Y}_{IMP})$ exist in the literature; however most surveys have not implemented them yet. There are three basic approaches to estimate $V\,(\hat{Y}_{IMP})$: multiple imputation (Rubin 1987), model assisted approach (Särndal 1990; Rancourt, Lee and Särndal 1993; Lee, Rancourt and Särndal 1994), and adjusted jackknife method (Rao and Shao 1992).

2.3 Weight Adjustment for Nonresponse

The approach that is frequently used to produce estimates in the presence of total nonresponse is often referred to as *reweighting*. In this case only the responding units are used to produce the estimates and their design weights are inflated to compensate for the nonresponse. The estimator of Y becomes

$$\hat{Y}_{RW} = \sum_{s_R} w_k \, wa_k \, y_k \, , \tag{8}$$

where wa_k is the *weight adjustment* of the unit k in s_R .

Weight adjustments are usually calculated as inverse response rates in *adjustment cells* or *weighting classes*. The adjustment cells must be carefully determined so that the bias of $\hat{Y}_{RW}$ is minimized. If for every adjustment cell, the units falling into the set s_R represent a random subsample of units originally selected, or equivalently if an assumption of a constant response probability within each cell holds, then the bias of the estimator (8) is negligible. This response model is sometimes referred to as the *uniform response mechanism.* The cells can be determined before the sample is selected, by dividing the survey population into a fixed set of weighting classes, or after the sample is selected, by dividing the realized sample, and every cell should contain a sufficiently large sample. In practice the uniform response model within the cells will never hold exactly but the bias will be greatly reduced if the cells are carefully chosen. The variance of $\hat{Y}_{RW}$ is based on a reduced sample size n_R (n_R = number of respondents in s) and increased by the additional fluctuation of weight adjustments so it is larger than $V(\hat{Y})$, but the unbiased estimator of $V(\hat{Y}_{RW})$ can usually be derived.

Two examples of weight adjustment discussed above are:

i) unweighted adjustment calculated as
$$wa_k = n_{WAC}/n_{R,\,WAC} \text{ for unit } k \text{ in adjustment cell } WAC, \tag{9}$$
where n_{WAC} is the number of sampled units in the cell WAC and $n_{R,\,WAC}$ is the number of respondents in the cell WAC, and

ii) weighted adjustment calculated as
$$wa_k = (\Sigma_{s\cap WAC} w_k)/(\Sigma_{s_R\cap WAC} w_k) \text{ for unit } k \text{ in adjustment cell } WAC, \tag{10}$$

where $\sum_{s\cap WAC}$ is the summation over all sampled units falling into the cell WAC and $\sum_{sR\cap WAC}$ is the summation over all responding units falling into the cell WAC. Reweighting using weighting classes is, for example, discussed in Platek and Gray (1985) and Särndal, Swensson and Wretman (1992). In general, more complicated response models are possible under which the weight adjustment for unit k is the inverse of the probability that the unit k will respond.

If auxiliary data correlated with the variable y are available either for every unit in the population or at least for every unit in s, then they can be used to improve the estimation of Y, for example by post-stratification. Such an estimator can be written as

$$\hat{Y}_{RW,\,AUX} = \Sigma_{s_R} g_k' \, w_k \, wa_k \, y_k, \tag{11}$$

where g_k' is some sample dependent weight that uses the auxiliary data. The estimator (11) is more resistant against the bias than the estimator (8) when the response model used to derive the adjustments wa_k fails and also the variance of (11) is smaller than $V(\hat{Y}_{RW})$.

3. ASSESSMENT OF THE SOLUTIONS FOR REPEATED BUSINESS SURVEYS

3.1 Total Nonresponse in Repeated Business Surveys

A repeated business survey is a survey of a population of businesses that is repeated on a regular basis, for example every month, quarterly or annually, in order to measure the level and the changes in their economic activities. To measure the changes efficiently, the subsequent samples are not independent. Often the sample remains the same for a number of subsequent survey occasions (*e.g.*, for four quarters within a survey year) or the sample is only updated for births and deaths in the population between the two survey periods. Sometimes the sample is gradually refreshed by rotating out a portion of the sampled units and replacing them with units that were not previously selected. This process is referred to as *sample rotation* and is mainly used to lessen the burden on the respondents. In any case, there is usually a large overlap between subsequent samples.

Because a business that entered the sample at some point is likely to be surveyed on several survey occasions, its survey data may be available for some survey periods while not available for the periods when the business belonged to the set of nonrespondents. In addition, frames used for business surveys often contain auxiliary data, such as size measures or industrial classification, that are correlated with the survey variables. Given the choice of different imputation and reweighting techniques that are currently available for implementation at Statistics Canada, imputation has usually been used to treat the total nonresponse because the existing techniques can make a better use of all the auxiliary data than the existing reweighting methods. In the following paragraphs we will discuss the advantages and disadvantages of imputation and reweighting in the case of a repeated business survey.

3.2 Repeated Business Surveys and Imputation for Total Nonresponse

Even though imputation is mostly intended to impute missing and incorrect items for respondents, it has been often used to impute data for nonrespondents in repeated business surveys as well. In these surveys the nonrespondents are likely different from respondents and the existing imputation techniques can better utilize the available auxiliary data to reduce the bias due to nonresponse than the existing reweighting techniques.

If *longitudinal cumulation* is required then imputation is preferable over reweighting. Longitudinal cumulation is cumulation of data over several survey periods to provide information about a longer reference period. For example, quarterly data can be cumulated over the four calendar quarters to obtain annual data. Such an approach is becoming common because it saves resources spent on annual surveys and reduces burden to the respondents. In the case of imputation the data can be cumulated at the unit level and the annual estimates are easy to produce. Another advantage of imputation is that it produces a complete data set which makes the production of the estimates for different domains as well as the data analysis operationally easier.

On the other hand, there is a number of disadvantages of using imputation. Imputation increases the variance of the estimator; however, the naive variance estimator underestimates the true variance. The underestimation can be quite severe and may lead to wrong inference about the survey population. Alternative estimators of $V(\hat{Y}_{IMP})$ exist in the literature but have not been widely implemented yet. Their implementation can be quite involved especially when many survey variables are collected and a number of different imputation methods are used. The data analysis can be very misleading if imputed data are treated as observed data. The imputed data must be properly flagged so the analyst can distinguish it from the reported data.

When the set of nonrespondents is large, imputation may become a very costly and long process. This is especially true for large units that are often imputed manually but high nonresponse can also increase the time and cost needed to run an automated imputation system. Development of such an imputation system may also be more complex than development of an estimation module with a weight adjustment. More discussion on advantages and disadvantages of imputation for business surveys and different imputation methods are presented by Kovar and Whitridge (1995).

3.3 Repeated Business Surveys and Reweighting for Total Nonresponse

The method of weight adjustment applied to the responding units is intended to compensate for the nonresponse at the estimation stage and it is recommended in the literature as the method to treat the total nonresponse. Lepkowski (1989) suggested that "imputation can increase the variance of estimates more than weighting class adjustment" and gives results of some empirical comparisons of reweighting and imputation. One of the main advantages of reweighting is that an estimator of $V(\hat{Y}_{RW})$ can usually be derived which does not underestimate the true variance. Also, reweighting should be easier to implement - both the development and running of the reweighting module could be faster and cheaper than the implementation of a complex imputation system that includes manual resolution of units which cannot be imputed by the automated system.

On the other hand, reweighting requires that the weight adjustment classes, within which one can assume a constant response probability, exist and can be determined. If such classes cannot be determined then the estimator $\hat{Y}_{RW}$ will likely be seriously biased. In fact, nonrespondents differ considerably from respondents in many business surveys and it may be impossible to find a good set of the weight adjustment cells in such cases. Another drawback is that the traditional weight adjustments discussed in Section 2.3 cannot make use of all auxiliary data available for the nonrespondents in repeated business surveys. It should be mentioned that the disadvantages discussed in this paragraph could be overcome with the use of model-based reweighting presented by Binder, Michaud and Poirier (1994). However at this point their method requires more research before it could be implemented.

The result of reweighting a data set for respondents with a different weight adjustment for every survey occasion is not as practical for the user as the complete data set produced by imputation. If longitudinal cumulation is requested it can only be done at some aggregate level. In the previous example, when annual data was obtained by cumulating the quarterly data, the annual data for individual units could not be produced and the variance estimation of annual estimates would become more complicated.

4. EXAMPLE

The two methods for handling the total nonresponse will be compared using data from the Statistics Canada Quarterly Motor Carriers of Freight Survey (QMCF). QMCF is a quarterly survey of Canadian for-hire trucking companies that collects close to one hundred variables measuring their financial (revenues and expenses) as well as operating (*e.g.*, number of employees and equipment) characteristics for medium and large-sized companies. The sample is selected at the beginning of the year using a stratified simple random sampling design and remains unchanged for the four quarters. A new sample is selected at the beginning of each year. Thus the design currently does not incorporate population changes during the year and does not use rotation or any other method of controlling the overlap between consecutive years. This is mainly to keep the design simple while the survey has been undergoing many changes (questionnaire, frame, *etc.*) and has a tight production schedule. The strata are determined by three stratification variables: i) grouping of standard industrial classification codes (SICG) that divides the population into four groups (general freight, bulk, household movers, other specialized freight), ii) region (Atlantic, Quebec, Ontario, Prairies, British Columbia and Territories), and iii) size (two take-some strata and one take-all stratum of the largest companies).

The survey was redesigned for the 1994 reference year with a new questionnaire and new systems. The original strategy was to impute data for all nonrespondents. This decision was based on a number of factors: there existed a relatively rich base of historical and frame data, the Statistics Canada Generalized Edit and Imputation System (GEIS) suitable for imputing continuous data was available, the methodology staff was experienced in developing GEIS applications, the user preferred a complete data set, longitudinal cumulation to produce annual data was required, *etc.*

At the end of the collection period for the first quarter of 1994 the response rate was lower than expected; among the 501 companies selected from the universe of 1,718 there were 317 (63.3%) active responding units, 45 (9.0%) out-of-scope (OOS) units (companies not in trucking industry, out of business, *etc.*), and 139 nonrespondents (27.7%). About one third of nonrespondents were refusals, the other two thirds fell in the category of "data not available". The survey was facing the following problems with the imputation strategy. The running of the GEIS system would be long and costly because of the increased volume of data to be imputed and a relatively small pool of donors of good data. The number of units requiring very costly manual imputation would also increase. The variance estimates would severely underestimate the true variances because the current version of the Statistics Canada Generalized Estimation System (GES,) used for the QMCF estimation, does not take imputation into account. Some correction of the GES variance estimates could be done but it would require substantial time for research and development of an additional estimation module. The correlations between the auxiliary variables and the survey variables were found lower than expected and therefore the quality of the imputed data became questionable.

The original strategy of imputing for total nonresponse was revisited and the alternative - reweighting - was considered. A number of issues arose. Should weight adjustments be applied for take-all units representing themselves? Are there any out-of-scope units among the nonrespondents? Do any suitable weighting classes exist?

In the sample of 501, there were 173 take-all's out of which 41 (23.7%) did not respond and 7 (4%) were OOS. It has been decided that the data for the take-all units in s_N would still be imputed mainly because these are the largest units and it would be difficult to determine weighting classes such that the respondents and nonrespondents could be assumed alike within these classes. Therefore it was felt that imputation will cause less nonresponse bias for these units than reweighting. In addition, the take-all units do not contribute to the sampling variance of the estimate and therefore the variance underestimation is not a concern here. Finally, a complete data set for take-all's facilitates better longitudinal comparisons of these units that are often of interest to the users. The drawback of this decision is the cost and time of imputing for 41 take-all nonrespondents.

During the collection period, 45 units among the 501 were identified as out-of-scope since they either were not trucking companies or were out of business. Different assumptions could be made about the units in s_N : A) all nonrespondents are in scope for the survey; B) the proportions of OOS units are similar for both respondents and nonrespondents; and C) some nonrespondents are OOS but their proportion is different from the proportion of OOS among respondents. Under assumption A, the weights would be adjusted for in-scope respondents but not for the OOS units. Under assumption B, the same adjustment would be applied to in-scope and OOS units within a weighting class. A study to determine the different proportions would be needed for assumption C.

Thus under assumption A, the weight adjustment for the in-scope respondent k that belongs to the weight adjustment cell WAC becomes

$$wa_k = \{\Sigma_{h\in WAC}\,(N_h/n_h)\,(n_{h,R} + n_{h,N})\}\ /\ \{\Sigma_{h\in WAC}\,(N_h/n_h)n_{h,R}\}, \qquad (12)$$

where $\Sigma_{h\in WAC}$ is the summation over all strata that form the cell WAC, N_h/n_h is the design weight in stratum h, $n_{h,R}$ is the number of in-scope respondents and $n_{h,N}$ is the number of nonrespondents in stratum h. Note that $n_h = n_{h,R} + n_{h,N} + n_{h,OOS}$, where n_h is the sample size in stratum h and $n_{h,OOS}$ is the number of OOS units in stratum h.

Under assumption B, the weight adjustment applied for the in-scope respondents as well as the OOS units in the cell WAC is

$$wa_k = \{\Sigma_{h\in WAC}\,N_h\}/\ \{\Sigma_{h\in WAC}\,(N_h/n_h)\,n_{h,R}\}, \qquad (13)$$

where N_h is the population size in stratum h. The choice between (12) and (13) depends on which assumption is more realistic given the survey collection and follow-up procedures.

To determine the adjustment cells, stratum population and sample sizes as well as response rates were examined. Since strata were designed as homogeneous groups they (or their groupings) were considered as classes for reweighting. Unfortunately many strata were small or required large adjustments, as for instance a stratum with $N_h = 17, n_h = 4, n_{h,R} = 2,\ n_{h,N} = 2$ and $n_{h,OOS} = 0$ where $wa_k = 2$. The same was true for classes at the SICG-by-region level. The only other suitable candidate seemed to be the SICG groups. However the validity of the assumption of constant response probability within each SICG group was questionable. The stratum response rates, for example, varied between 100% and 25% within one SICG group.

Three sets of estimates were calculated: 1) estimates based on data imputed for all nonrespondents ($\hat{Y}_{IMP}$), 2) estimates based on reweighting using assumption B and strata as the adjustment cells ($\hat{Y}_{RW}$), and 3) estimates based on reweighting using strata as the cells and post-stratification with the estimated number of in-scope units for each SICG from the full sample as a benchmark ($\hat{Y}_{RW,AUX}$). The national estimates of in-scope units and total revenues are given below. It should be noted that these were the estimates that were easy to be implemented using the GES software.

The first and the third estimates in Table 1 are the same for the number of in-scope units and quite similar for the total revenues (< 2% difference) because they are both based on assumption A while the second estimate is different since it is based on assumption B. Under B, weights of in-scope as well as OOS units are adjusted and therefore the share of OOS units increases while the share of in-scope units drops when compared with assumption A. Similar observations were made when comparing regional estimates. However the first and the third estimates of in-scope units were not equal because poststrata were defined as SICG groups. The estimated coefficients of variation of $\hat{Y}$ were calculated in GES and hence are based on the naive variance estimates. The cv's in Table 1 are almost the same and similarly, the estimated cv's of the regional revenue estimates were found very similar. Yet we know that $v_{NAIVE}(\hat{Y}_{IMP})$ underestimates $V(\hat{Y}_{IMP})$ while the estimates of $V(\hat{Y}_{RW})$ and $V(\hat{Y}_{RW,AUX})$ are likely biased because the assumption of constant response probability within strata does not hold and there was only one respondent in some strata.

Given the problems with finding appropriate weight adjustment cells and the fact that research and software would be required to implement a more complex form of reweighting, imputation was chosen over reweighting in this example. Complete data sets are also more suited for the user's needs and facilitate better the production of annual figures. A temporary solution to the variance underestimation problem was implemented: estimated variances are increased by using inflation factors as suggested by Kovar and Chen (1994); these factors depend on the imputation rate. This solution should be replaced by the proper variance estimator in the future.

Table 1: Comparison of National QMCF Estimates for the First Quarter of 1994

Estimate	Estimated Number of In-Scope Units	Est. Total Revenues $\hat{Y}$ (million \$)	cv($\hat{Y}$)
$\hat{Y}_{IMP}$	1,514	2,514	.030
$\hat{Y}_{RW}$	1,419	2,457	.029
$\hat{Y}_{RW,AUX}$	1,514	2,554	.029

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