

Practical Criteria for Definition of Weighting Classes

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ABSTRACT

When the technique of adjustment using weighting classes is applied to compensate for the effect of non-response, several questions arise that call for precise and quantified answers: How does the choice of the variables used for definition of the classes affect total root-mean-square error, in particular non-response bias and sampling variance? What rule and what procedure should be followed in choosing the adjustment variables? On the basis of what criterion can the optimal sizes for the weighting classes be established? Finally, when this procedure is applied to compensate for non-response with respect to specific elements of a questionnaire, how can strongly correlated ancillary variables be used effectively when they themselves are affected by non-response? This article is addressed to those professionals working at a practical level who are seeking guidelines.

KEY WORDS: Adjustment for non-response; Weighting classes; Poststratification; Non-response bias.

1. INTRODUCTION

The problem of adjustment for non-response through creation of weighting classes is clearly related to that of determination of poststratification criteria. Kish (1978) stated that there was an urgent need for research in this area, noting that, in terms of advantages and disadvantages, the final effect of this type of weighting is often unknown. At the same time, Platek, Singh and Tremblay (1978) developed mathematical expressions for the bias and the variance of the estimators resulting from adjustment using weighting classes. Their model, which was based on the response-probability concept, was developed further recently by Platek and Gray (1983). During the same period, Bailar, Bailey and Corby (1978) described the theoretical and empirical research undertaken at the US Bureau of the Census. They end their presentation by emphasizing the importance and the necessity of developing solid theoretical foundations for the methods of adjustment for non-response. More recently, the Panel on Incomplete Data (1983) provided a particularly concise and complete description of the practical implications of adjustment through weighting and stressed the conclusions reached by Oh and Scheuren (1983) following a simulation study. Chapman (1983) analysed a number of procedures that could be used to identify the most relevant variables for effective construction of weighting classes.

This article continues along the same lines as these research efforts by attempting to define some rules for application of this adjustment procedure starting from theoretical foundations. The single example used for illustration throughout this text is very specific, but the reader will no doubt be able to identify much more varied and rich application possibilities.

2. ILLUSTRATION OF THE TECHNIQUE

Let us take as our example the measurement of voters' intentions, a very real and frequently encountered problem. All of the data used in this text comes from the fall 1985 OMNIBUS survey of the Survey Research Centre at the University of Montreal. One section of this survey was aimed at measuring voters' intentions four weeks before the December

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Table 1
Distribution of Voting Intentions
(with Non-Response)

	<i>n</i> ^a	%
Parti Québécois (PQ)	505	27.5
Quebec Liberal Party (QLP)	650	35.4
Other parties	62	3.4
Non-response	619	33.7
TOTAL	1,836	100.0

^a Number of weighted cases.

Table 2
Satisfaction with the Quebec Government and Voting Intentions
with Regard to the Provincial Election

Voting intentions	Satisfied (<i>n</i> = 555)	Dissatisfied (<i>n</i> = 656)
PQ	70.1%	17.3%
QLP	26.7%	76.1%
Other	3.2%	6.6%

1985 Quebec elections. The responses to the question regarding voting intentions given by the 1,836 individuals surveyed who intended to vote were distributed as in Table 1.

This table presents a situation where the response problem obviously cannot be ignored. Blindly distributing the non-responses in proportion to the other responses is a risky approach based on the supposition that those who did not express their voting intentions have the same profile as those who answered the question spontaneously.

The two consequences of such a high incidence of non-response are well known: potential bias and an increase in sampling error following effective reduction of sample size. Any adjustment technique must be aimed at reducing these two effects. When, as in this case, a high incidence of non-response can be foreseen, it is appropriate to include in the questionnaire correlated questions that can be used as a basis for eventual adjustments. For example, it may be very useful to ask the persons surveyed whether or not they are satisfied with the current government, given the close connection between this index and voting intentions, as shown in the following table.

As Table 2 shows, 70.1% of those satisfied with the government intended to support the party in power (the PQ). However, as might be expected, the situation was reversed among those who were dissatisfied: 76.1% of this number intended to vote for the QLP, which was the opposition party at the time.

Table 3
Satisfaction with the Government Cross-Classified with Whether Or Not an Answer Was
Given to the Question Regarding Voting Intentions (Number of Weighted Cases)

	Satisfied	Dissatisfied	TOTAL
Answer given to question regarding voting intentions	$n_1 = 555$	$n_2 = 656$	$n = 1,211$
No answer given to question regarding voting intentions	236	334	570
TOTAL	$n'_1 = 791$	$n'_2 = 989$	$n' = 1,780^a$

^a This table excludes 56 nonresponses to the question on the satisfaction.

One of the techniques available for using this ancillary information is the creation of weighting classes based on satisfaction. Table 3 presents the complementary data required for making the adjustments.

If those who were satisfied and those who were dissatisfied are regarded as two weighting classes, statistical adjustment of the data takes the following form:

if p_{jc} = the proportion of respondents in class c who intend to support party j ;
 n_c = the number of persons in class c who answered the question regarding
voting intentions;
 $n = \sum_c n_c$ = the size of subsample S_1 of those who answered the questions regarding
voting intentions and satisfaction;
 n'_c = the total number of persons in class c ;
and $n' = \sum_c n'_c$ = the size of sample S of those who answered the question regarding
satisfaction

The adjusted estimates of voting intentions are then calculated as follows:

$$p_j = (1/n) \sum_c n'_c p_{jc}.$$

This new estimate corresponds to introducing a corrective weight equal to $n'_c n / n_c n'$ for all respondents in class c .

This simple exercise illustrates the functioning of the well-known mechanism of statistical adjustment through construction of weighting classes based on traditional poststratification procedures. The questions which must be gone into in more depth for such an application are as follows:

1. What is the impact of this procedure on reduction of non-response bias?
2. How does this technique affect sampling error?
3. What are the best ancillary variables (or combinations or variables) for definition of the classes?
4. Up to what point is it advantageous to refine definition of the weighting classes?
5. What should be done with ancillary variables that also involve non-response?

To answer these questions properly, we must continue to develop the theoretical foundations for application of weighting classes.

3. IMPACT OF ADJUSTMENT PROCEDURE ON NON-RESPONSE BIAS

The most difficult challenge with respect to non-response is that of quantifying reduction of non-response bias following application of a given technique. If this challenge could be met, it would be possible to measure the bias and, consequently, to produce unbiased estimates.

However, we can still endeavour to understand more fully the mechanisms underlying non-response, in order to design instruments that would reduce as much as possible the impact of non-response on data quality.

One way of studying the problem is to consider it from the angle of response-probability theory, according to which we would stipulate that, for each unit U_i of the population, the probability of responding to the survey (or to a specific question asked) is α_i if that unit is selected. Even though this approach calls for the supposition that the α 's are not nil, the theory allows us to infer mathematical expressions for non-response bias with the application of a given method, in function of the observations X_i that we want to obtain and of the response probabilities α . This was the approach taken by Platek and Gray (1983); for estimating subtotal in weighting class c , by adjusting the sampling estimation using the inverse of the response rate in class c , they established that residual non-response bias could be expressed as follows:

$$B(\hat{X}_c) = \bar{\alpha}_c^{-1} \sum_{i=1}^{N_c} (\alpha_i - \bar{\alpha}_c) X_i \quad \text{where } \bar{\alpha}_c = N_c^{-1} \sum_{i=1}^{N_c} \alpha_i \quad (3.1)$$

and where N_c = the size of class c of the population.

Expression (3.1) reminds us that residual non-response bias exists following application of the correction factor only if, within class c , there is a correlation between the response probabilities and the characteristic measured.

Moreover, it is interesting to examine expression (3.1) in the special context of classification data—that is, where the $X_i = 0$ or 1. Using the notation introduced in the preceding section, it can be shown that the residual bias of \hat{X}_c following application of the correction factor can be written on the basis of expression (3.1) in the following form:

$$\begin{aligned} B(\hat{X}_c) &= N_c P_c \bar{\alpha}_c^{-1} (\bar{\alpha}_c^x - \bar{\alpha}_c) \\ &= N_c P_c (1 - P_c) \bar{\alpha}_c^{-1} (\bar{\alpha}_c^x - \bar{\alpha}_c^{\tilde{x}}); \end{aligned}$$

where P_c = the real proportion of the units in class c that have characteristic X ;

$\bar{\alpha}_c^x$ = the average for response probabilities among the units in class c that have characteristic X ;

and $\bar{\alpha}_c^{\tilde{x}}$ = the average for response probabilities among the units in class c that do not have characteristic X .

It is useful to reformulate $B(\hat{X}_c)$ as follows:

$$B(\hat{X}_c) = N_c \sigma_c^2 d_c(X, \tilde{X})$$

where σ_c^2 = is the variance of characteristic X within class c

and $d_c(X, \tilde{X}) = \bar{\alpha}_c^{-1} (\bar{\alpha}_c^x - \bar{\alpha}_c^{\tilde{x}})$ is a standardized measurement of the distance between the average response probability for those who have characteristic X and that for those who do not have it within class c .

The non-response bias associated with estimation p' of P can therefore be expressed as:

$$\begin{aligned} B(p') &= B(N^{-1} \sum_c \hat{X}_c) \\ &= N^{-1} \sum_c N_c \sigma_c^2 d_c(X, \hat{X}), \end{aligned} \quad (3.2)$$

Expression (3.2) provides a mathematical argument in support of the thesis frequently put forward that it is advantageous to construct categories that are as homogeneous as possible with respect to the phenomenon studied by partitioning the sample into segments, some of which tend to contain units with characteristic X , and some of which do not.

4. IMPACT OF ADJUSTMENT PROCEDURE ON SAMPLING ERROR

As you know, one of the consequences of the non-response problem is an increasing of random sampling error following reduction in the number of observations. It is revealing to examine to what extent the adjustment technique discussed here compensates for this loss of precision. A number of the authors referred to in the introduction have pointed out the potential danger in having corrective weights that are too large or too unstable, being based on a number of observations within a class that is too limited. Platek and Gray (1983) presented an approximate expression for the component of variance attributable to non-response following adjustment.

Although it is instructive regarding the general behaviour of this component of sampling variance, this mathematical development does not reveal the critical point beyond which refinement of the weighting classes adversely affects data accuracy.

In reality, we find ourselves in the following situation. The person conducting the survey has some reliable information with respect to a representative sample of the population being studied (for example, information regarding satisfaction with the government), but the data that interest him or her most for purposes of the survey (for example, information regarding voting intentions) are available only for a subsample, and he or she would like to use certain data from the base sample to improve the accuracy of the estimators. Whether we are talking about non-response at the level of the sampled units or about non-response at the level of specific questions in a questionnaire, the fundamental problem is the same. From the point of view of estimator variance, there is some analogy with double sampling, where data adjustment corresponds to application of the separate-ratio estimators—that is, to poststratification using categories definable on the basis of information available in the base sample. Of course, this analogy is unacceptable as far as analysis of the biasing effect of non-response is concerned, since one cannot support the hypothesis that the subsample of the respondents is probabilistically representative of the base sample. However, for purposes of studying estimator variance, the analogical approach is as useful as it is defensible.

More specifically, imagine the following situation. A simple random sample S of size n' gives us the distribution of a classification variable for the total population, with $\hat{N}'_c = (N/n')n_c$ as the estimator of the number of units of the population belonging to class c . A simple random sample $S_1 \subset S$ of size $n = fn'$ ($0 < f < 1$) is chosen to measure the distribution of another classification variable X . For each of the units of S , we know the classification on the basis of the two variables described above.

We want to estimate the proportion P_j of units belonging to class j of variable X . The simple estimator inferred from S_1 is

$$p_j = (1/n) \sum_c n_c p_{jc}.$$

Moreover, the separate-ratio (poststratified) estimator can be expressed as follows:

$$p_j' = (1/n') \sum_c n_c' p_{jc}$$

While all the units of sample S_1 are given a weight equal to 1 in expression p_j , we can see that, in expression for p_j' , the weight of the units varies, depending on the c class to which they belong. These "corrective" weights equal to $n_c' n/n_c n'$ use the complementary information available with respect to sample S as a whole for division into classes.

According to Tremblay (1975), if the formula for the variance of p_j is developed, keeping the terms to the size of the relative variance of the \hat{N}_c , the following is obtained:

$$\text{Var } p_j = \text{Var } p_j - [(1-f)/n] \left[\sum_c (P_{jc} - P_j)^2 P_c - \sum_c r_c P_{jc} (1 - P_{jc}) P_c \right] \quad (4.1)$$

where $r_c = N(1 - P_c)/nN_c$: the relative variance of the N_c estimator that is, $\hat{N}_c = (N/n)n_c$;

$P_{jc} = N_c/N$: the proportion of the population belonging to class c ;

$P_{jc} = Ep_{jc}$: the proportion of the units that have characteristic j in class c ;

$P_j = Ep_j$: the proportion of the units of the population that have characteristic j .

Equation (4.1) shows that the effectiveness of the technique of adjustment using weighting classes increases as interclass variance increases and, consequently, as intraclass variance decreases. It is easy to verify that, in the extreme case where there is maximal interclass variance - that is, where all of the P_{jc} are either 0 or 1:

$$\text{Var } p_j = P_j(1 - P_j)/n'.$$

that is, the variance that would have been obtained if all of the n' units had responded.

In addition, equation (4.1) reminds us that, in so far as the relative variances are negligible with respect to 1, it is advantageous to refine the partitioning, dividing the sample into a large number of classes. We thereby increase interclass variation and, by the same token, reduce the variance of p_j' .

However, refinement of the partitioning is limited by the presence of relative variances r_c . We should look at this situation a little more closely. Let us postulate that a first partitioning of the sample into a group of classes C' produces estimator p_j' as previously defined. Then let us postulate that a second, more refined partitioning C'' allows for the construction of estimator p_j'' . If all of the classes coincide with the classes, except for one c class divided into two parts (c_1 and c_2 that is, $c = c_1 \cup c_2$), it would be interesting to find a simple criterion for determining which of the two partitions (C' or C'') produces the smallest variance, taking into account the r_c factors in expression (4.1) above. We know that:

$$\begin{aligned} \text{Var } p'' &< \text{Var } p' \\ \Leftrightarrow G &= \sum_{c \in C''} (P_{jc} - P_j)^2 P_c - \sum_{c \in C'} (P_{jc} - P_j)^2 P_c \\ &> \sum_{c \in C''} r_c P_{jc} (1 - P_{jc}) P_c - \sum_{c \in C'} r_c P_{jc} (1 - P_{jc}) P_c = D. \end{aligned}$$

The left-hand member G of the inequality can be expressed thus:

$$\begin{aligned} G &= \sum_{c \in C''} P_{jc}^2 P_c - \sum_{c \in C'} P_{jc}^2 P_c \\ &= P_{jc_1}^2 P_{c_1} + P_{jc_2}^2 P_{c_2} - P_{jc}^2 P_c. \end{aligned} \quad (4.2)$$

If class c has been partitioned in the following way:

$$n_{c_1} = an_c \text{ and } n_{c_2} = (1-a)n_c \text{ when } 0 < a < 1$$

we know that $P_{jc} = aP_{jc_1} + (1-a)P_{jc_2}$, that $P_{c_1} = aP_c$, and, finally, that $P_{c_2} = (1-a)P_c$. Expression (4.2) can therefore be written compactly as follows:

$$G = P_c a(1-a) [P_{jc_1} - P_{jc_2}]^2.$$

Moreover, the right-hand member can be reduced to:

$$D = r_{c_1} P_{jc_1} (1 - P_{jc_1}) P_{c_1} + r_{c_2} P_{jc_2} (1 - P_{jc_2}) P_{c_2} - r_c P_{jc} (1 - P_{jc}) P_c.$$

With respect to the relevance of refining the partitioning, by replacing relative variances r_c with the expression previously established, noting that the terms P_{c_1} , P_{c_2} and P_c are negligible with respect to 1, we obtain:

$$D = (1/n) [P_{jc_1} (1 - P_{jc_1}) + P_{jc_2} (1 - P_{jc_2}) - P_{jc} (1 - P_{jc})]$$

Because of the convexity of function $P(1-P)$ and the fact that P is a linear combination P_{jc_1} and P_{jc_2} , the value of D is limited in an upwards direction by $1/4n$. Thus, for the variance of p'' to be smaller than that of p' , it is sufficient that:

$$P_c a(1-a) [P_{jc_1} - P_{jc_2}]^2 > 1/4n.$$

If P_c is estimated using n_c/n on the basis of subsample S_1 , this condition takes the following form:

$$DIF = |P_{jc_1} - P_{jc_2}| > \frac{1}{2} \sqrt{a(1-a)n_c} = DIFMIN \quad (4.3)$$

Inequality (4.3) therefore reveals a simple rule that is sufficient to make it advantageous to divide class c into $c_1 \cup c_2$. As we might have expected intuitively, the larger the number

Table 4.Values of $DIFMIN = \frac{1}{2}\sqrt{a(1-a)}n_c$ (in %))

n	$a = 1/2$	$a = 1/4$	$a = 1/10$
1000	3.1%	3.7%	5.3%
400	5.0%	5.8%	8.3%
200	7.1%	8.2%	11.8%
100	10.0%	11.5%	16.7%
80	11.2%	12.9%	18.6%
60	12.9%	14.9%	21.5%
40	15.8%	18.3%	26.4%
20	22.4%	25.8%	37.3%
15	25.8%	29.8%	43.0%
10	31.6%	36.5%	52.7%

of respondents in class c (in sample S_1) or the greater the difference between the P_{jc_1} and P_{jc_2} proportions, the more advantageous it is to refine the partitioning of the classes. Table 4 above presents the minimal differences ($DIFMIN$) corresponding to various values of n_c and a .

The above table tells us that, for example, if we have a class containing 100 respondents which we are considering dividing into two more or less equal parts, there must be a difference of at least 10% between the two new classes where the j characteristic is concerned if the refinement of the partitioning is to help reduce sampling error. If there is less than a 10% difference between the two, refinement will serve no purpose, and may even increase the variability of the estimates produced. Moreover, we can see that if subclasses c_1 and c_2 are very unequal, the requirement regarding differentiated behaviour of their respondents with respect to characteristic j (that is P_{jc_1} vs P_{jc_2}) is stronger. Thus, if c_1 represents approximately 10% of c , the minimal difference ($DIFMIN$) is 16.7%.

In the specific case where class c is divided more or less equally between c_1 and c_2 , the minimal difference ($DIFMIN$) can be expressed very compactly:

$$DIFMIN = 1 / \sqrt{n_c}$$

In situations where class c is divided into several components ($c = c_1 U c_2 U \dots U c_k$), we can apply the test described here, considering the smallest of subclasses c_j on the one hand, and all of the rest on the other. Since, in this case, a (or $1-a$) may be small, we can simplify the rule expressed by inequality (4.3) and consider the minimal difference as follows:

$$DIFMIN = \frac{1}{2} \sqrt{\min_j (n_{c_j})}$$

It should be noted here that these results were developed by analogy in the context of sampling in two phases, and that the rules which have been arrived at may apply both to separate-ratio estimators and to poststratified estimators. For example, it is often useful to determine up to what point refinement of a poststratification produces more precise results. The rules set out here may therefore serve as a guide.

5. CRITERION FOR CHOOSING ADJUSTMENT VARIABLES

Looking once more at the survey of voters' intentions, we see that the degree of satisfaction with the government can certainly serve as an adjustment variable for non-response with respect to the question regarding voting intentions. However, is this really the best variable we could use? If the survey instrument contains other questions connected indirectly with voting intentions, on the basis of what criterion can we choose between, for example, satisfaction, certain sociodemographic profiles (language, education) and the perception as to who would make the best premier?

The two preceding sections show us that the more homogeneous the constructed classes are, the more variance of the adjusted estimates is reduced and the more likely it is that the bias itself will be smaller. It is therefore advantageous to create classes that maximize interclass variance of estimator p_j . With respect to algebraic expression (4.1), the partitioning chosen must maximize the quantity

$$INTERCL_j = \sum_c (P_{ic} - P_j)^2 P_c$$

For a multinomial variable X with parameters P_1, P_2, \dots, P_J , the problem is finding a statistic that incorporates all of the *INTERCL* quantities ($j = 1, \dots, J$). In this case, χ^2 merits consideration, since

$$\chi^2 = N \sum_j \sum_c (P_{jc} - P_j)^2 P_c / P_j = N \sum_j P_j [INTERCL_j / P_j^2]$$

In other words, χ^2 is equal to a linear combination of the relative values of the *INTERCL_j*'s weighted in function of the P_j 's. On the other hand, since $B_j = INTERCL_j / P_j(1 - P_j)$ measures the proportion of the variance explained by division into classes, there is also justification for considering the statistic

$$\sum B_j = \sum_j \sum_c (P_{jc} - P_j)^2 P_c / P_j(1 - P_j).$$

Note that the latter statistic is equivalent to χ^2 in three specific situations: a) when X is dichotomous; b) when the P_j 's are almost equal; and c) when the P_j 's are all small. In the multinomial case, where it is important to refine estimation of a P for a particular j index, we can therefore dichotomize variable X in function of this j index and use χ^2 as a performance criterion for division into classes. For our example, we will use χ^2 , since this statistic is produced directly by most of the software used for processing survey data.

6. APPLICATION AND INHERENT PROBLEMS

In the preceding discussion, we found a criterion for evaluating the performance of weighting classes. In practice, however, variables which best explain variance may also be affected by the non-response problem. This complicates the choosing of weighting classes to some extent.

The following table presents a list of variables deemed interesting a priori by a researcher for the purpose of weighting to adjust for non-response with respect to the voting-intentions

question. For each potentially useful variable, there is a description of the value of χ^2 , the number of missing values and the total number of missing values when the variable is crossed with the question on voting intentions. Remember that the latter question, taken alone, accounted for 619 non-responses in the survey.

The value of χ^2 is very revealing with respect to the predictive force of the different variables involved. For example, we can see that, among the sociodemographic variables, only mother tongue has an impact that merits attention. On the other hand, some thematic questions show an unequivocal link with voting intentions – in particular, that regarding degree of satisfaction with the present government and that which asks which of the two main party leaders would be the best premier. It is clear that the more a question is perceived as being connected with the basic question, the more difficult it is to obtain responses. Only 56 non-responses were recorded for the more insignificant question regarding satisfaction with the government (approximately 3% of the sample), but there were 392 non-responses when people were asked who would be the best premier!

In the creation of weighting classes, it is therefore advantageous to try to use variables strongly correlated with the phenomenon being studied, as well as variables which are both strongly correlated and characterized by an excellent response rate. In addition, by crossing the relevant variables with each other, we can create classes that are more homogeneous and, consequently, increase the value of χ^2 . Obviously, the degree of refinement of the classes must be in line with the limiting criterion previously expressed by equation (4.3).

Table 5

List of Variables That Might Be Useful for Compensation, through Weighting, for the Effect of Non-Response with Respect to the Question on Voting Intentions

Variable ^a	Value of χ^2	Number of missing data on the variable	Number of missing data upon cross-classification with voting intentions
Age (6)	34	4	620
Education (4)	8	3	621
Mother tongue (2)	96	0	619
Degree of satisfaction with Quebec government (4)	382	56	625
Degree of satisfaction with Quebec government (2)	346	56	625
Identification of best premier (3)	773	392	686
Vote in 1981 provincial election	109	269	658
Interest in politic	1	1	619
Degree of satisfaction with federal government (4)	39	58	631
Voting intentions at federal level (4)	288	694	832

^a The figures in parentheses indicate the number of classes considered for the variables in question.

Consider, for example, the formation of weighting classes on the basis of three variables that are explanatory with respect to voting intentions – namely, identification of the party leader who would be the best premier (3 response categories), degree of satisfaction with the government (4 categories) and mother tongue (2 categories). At this stage, the idea is to project the voting intentions determined for the respondents in a given class onto all of the individuals in that class – that is, those for whom it has been possible to establish a classification. The first step in the process is to refine the classes as much as possible on the basis of the three variables involved and produce a cross tabulation of voting intentions in accordance with these twenty-four (3x4x2) classes. Referring either to the criterion revealed in equation (4.3) or to Table 4, we eliminate through combination those classes which are too small. Where necessary, we therefore group together “similar” classes – that is, classes that have a similar voting-intentions profile. We are then in a position to produce a table like that on the following page, in which voting intentions are cross-classified following this new division. An examination of the data may also suggest a few groupings. In addition, Table 6 presents other relevant data. For example, the last two lines compare by class the number of individuals who answered the question regarding voting intentions with the total number of individuals surveyed who can be classified in accordance with the three variables involved. From this, we obtain a first weighting system. In the example, there are 283 persons overall who can be classified, but whose voting intentions are not known. In addition, the overall value of χ^2 is 891, a distinct improvement over the situation when the variables were taken alone (Table 5).

Finally, in the B_j column, for each P_j , there appear estimates of the percentage of the variance that can be attributed to interclass variance. These B_j 's measure the increase in precision (variance reduction) that can be attributed to adjustment of the data in accordance with the type of partition chosen. This is clear if we rewrite equation (4.1) as follows (disregarding relative variances):

$$\text{Var } p'_j = \text{Var } p_j - (1 - f)B_j \text{Var } p_j$$

Having a B_j equal to 61.9% for estimation of intention to vote for the PQ means that, from the point of view of variance reduction, adjustment of the data is equivalent to having recuperated in the field 61.9% of the 283 non-responses for the question on voting intentions.

We now have the residual problem of determining how to adjust for non-response for specific questions using variables that have themselves been affected by non-response.

In the example produced through division in accordance with Table 6, it is clear that a significant portion of the non-responses with respect to voting intentions is not corrected through this kind of weighting. In effect, we are left with 409 cases of non-response that cannot be dealt with in this fashion, since classification with respect to a reference variable cannot be determined. One possibility that might be explored here is establishment of a weighting system that would allow us to use, for each non-respondent, the maximum number of variables available for estimating the missing data. For example, the voting-intentions profile of persons who did not respond to the question on voting intentions or to that asking who would be the best premier, but who we know are Francophone and are satisfied with the government in power, would be inferred on the basis of the voting-intentions profile of the Francophone respondents satisfied with the government. A weighting system can easily be developed for this process of attribution.

Table 6.
Study of a Partitioning of the Sample

Best premier		Johnson (PQ)			
Satisfied government	Very	Fairly	Very or Fairly	Not very or not all all	
Mother tongue	Franco-phone	Franco-phone	Non-franco-phone	Franco-phone	Non-franco-phone
% vote PQ	100	88.3	42.7	63.4	32.9
% vote PLQ	0.0	9.5	45.8	30.2	61.4
% vote Other	0.0	2.2	11.5	6.4	5.7
Number of respondents for the classification and voting-intentions questions	51	342	37	133	22
Number of respondents for the classification questions	59	404	50	203	28
Best premier		Bourassa (PLQ)			
Satisfied government	Very or fairly		Not very		Not at all
Mother tongue	Franco-phone	Non-franco-phone	Franco-phone	Non-franco-phone	Franco-phone
% vote PQ	12.2	0.0	6.5	1.2	3.5
% vote PLQ	86.5	85.9	92.4	98.8	93.9
% vote Other	1.3	14.1	1.1	0.0	2.6
Number of respondents for the classification and voting-intentions questions	64	21	156	49	159
Number of respondents for the classification questions	81	24	178	54	175
Best premier	Other than Johnson	Neither Bourassa nor Johnson		TOTAL	B_j (%)
Satisfied government	Not at all	Very or fairly	Not very or not all all		
Mother tongue	Non-franco-phone	----	----		
% vote PQ	0.0	14.3	4.6	42.7	61.9
% vote PLQ	100.0	73.5	54.9	52.6	58.7
% vote Other	0.0	12.2	40.5	4.7	15.1
Number of respondents for the classification and voting-intentions questions	42	17	51	1144	($\chi^2 = 891$)
Number of respondents for the classification questions	49	32	89	1427	

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