AN APPLICATION OF REGRESSION AND CALIBRATION ESTIMATION TO POST-STRATIFICATION IN A HOUSEHOLD SURVEY

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ABSTRACT

This paper empirically compares three estimation methods—regression, calibration, and principal person—used in a household survey for post-stratification. Post-stratification is important in many household surveys to adjust for nonresponse and the population undercount that results from frame deficiencies. The correction for population undercoverage is usually achieved by adjusting estimated people counts in each post-stratum to equal the corresponding population control counts typically available from an external source such as a census. We will compare estimated means from the three methods and their estimated standard errors for a number of expenditures from the Consumer Expenditure Survey sponsored by the Bureau of Labor Statistics in an attempt at understanding how each estimation method accomplishes this step in post-stratification.

1. INTRODUCTION

In large household surveys, post-stratification is a means of reducing mean square errors by adjusting for differential response rates among population subgroups and frame deficiencies that often result in undercoverage of the target population. In general, the population is subdivided into groups (post-strata) at the estimation stage based on information that affect the response variables. The estimator is constructed in such a way that the estimated total number of individuals falling into each post-stratum is equal to the true population count. Post-stratum population counts are typically available from an external census for numbers of persons but not for numbers of households. If household estimates are needed, a single weight must be assigned to each household while using the person counts for post-stratification. Regression estimators of totals or means accomplish this by using person counts in each household's auxiliary data. Calibration estimation, with a least-squares distance function, is closely related to regression estimation but controls extreme weights and can produce estimators with lower variance while still adhering to the population controls. An alternative used by some surveys is the principal person (PP) method (Alexander 1987) in which the household weight is based on the individual designated as the "principal person" in each household. Persons are classified into post-strata and person weights are ratio adjusted to achieve population control totals, leading to the possibility that each person in a household may have a different weight. The weight associated with the principal person is then assigned to the household. This ad hoc method is difficult to analyze theoretically. The regression estimator discussed in this paper, while easily adjusting for the population under count, automatically provides a household weight that is not based on any particular one of its members. Lemaître and Dufour (1987) address Statistics Canada's use of the regression estimator in this regard.

There are a growing number of precedents for the use of regression estimators in surveys both in the theoretical literature and in actual survey practice. Statistics Canada has incorporated the general regression estimator into its generalized estimation system (GES) software that is now used in many of its surveys. Fuller, Loughin and Baker (1993) discuss an application to the USDA Nationwide Food Consumption Survey. One of the attractions of regression estimation is that many of the standard techniques in surveys including the post-stratification estimator mentioned above are special cases of regression estimators. It also more flexibly incorporates auxiliary data than other more common methods. Other works related to regression estimation and post-stratification include Bethlehem and Keller (1987), Casady and Valliant (1993), Deville and Särndal (1992), Deville, Särndal, and Sautory (1993), and Zieschang (1990).

In this study we compare the regression estimator with the PP estimator currently in use at the Bureau of Labor Statistics (BLS). The ordinary least-squares regression estimator has the disadvantage that it can produce nonpositive weights. A number of ways are suggested in the literature on how to overcome this problem. Possibly the most flexible is the calibration method introduced by Deville and Särndal (1992) which can remove any negative weights as well as control extreme weights. The calibration estimators produced by these new weights are also compared to the original regression estimator and the PP estimator.

In Section 2, the three different estimators are presented. Section 3 is an application of these procedures to the Consumer Expenditure (CE) Survey at BLS—the same setting as in Zieschang (1990). We compare the distributions of the weights from the different methods as did Stukel and Boyer (1992) and also the coefficients of variation for a number of the survey target variables for the full population and for a number of domains. Section 4 provides a summary of our conclusions.

2. REGRESSION, CALIBRATION, AND PRINCIPAL PERSON ESTIMATION

First, we give a brief introduction to the regression estimator. A sample s of size n is selected from a finite population U of size N. Let the probability of selection of the i^{th} unit be π_i. The sample could be two-stage and the unit could be either the primary sampling unit or the secondary sampling unit. There is no need here to complicate the notation with explicit subscripts for the different stages of sampling. Let the variable of interest be denoted by y and suppose that its value at the i^{th} unit, y_i, is observed for each $i \in s$. Assume the existence of K auxiliary variables $x_1, x_2, \ldots, x_K$ whose values at each $i \in s$ are available. Define $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{iK})'$, for each $i \in U$, where x_{ik} denotes the value of the variable x_k at unit i. Let $\mathbf{X} = (X_1, \ldots, X_K)'$ denote the K-dimensional vector of known population totals of the variables $x_1, x_2, \ldots, x_K$. The regression estimator is then motivated by the working model ξ:

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_K x_{iK} + \varepsilon_i \tag{2.1}$$

for $i = 1, \ldots, N$. Here, $\beta_1, \ldots, \beta_K$ are unknown model parameters. The ε_i are random errors with $E_\xi(\varepsilon_i) = 0$ and $\mathrm{var}_\xi(\varepsilon_i) = \sigma_i^2$ for $i = 1, \ldots, N$. The term "working model" is used to emphasize the fact that the model is likely to be wrong to some degree. In the CE, y_i might be the total food expenditures by the consumer unit (CU) and the x_{ik}'s might be various CU characteristics like numbers of people of different ages, or CU income, that have an effect on the CU's expenditure on food. The variance of expenditures might be dependent on CU size so that having σ_i^2 proportional to the number of persons in the CU might be reasonable. Then, a linear regression estimator of the population total of y is defined to be

$$\hat{y}_R = \hat{y}_\pi + (\mathbf{X} - \hat{\mathbf{x}}_\pi)'\hat{\boldsymbol{\beta}} \tag{2.2}$$

where $\hat{y}_\pi$ denotes the π-estimator (or Horvitz-Thompson estimator) of the population total of y, i.e., $\hat{y}_\pi = \sum_{i \in s} a_i y_i$, where $a_i = 1/\pi_i$. Also, $\hat{\mathbf{x}}_\pi = (\hat{x}_{1\pi}, \ldots, \hat{x}_{K\pi})'$ is the vector of π-estimators of the population totals of the variables $x_1, x_2, \ldots, x_K$ and

$$\hat{\boldsymbol{\beta}} = (\hat{\beta}_1, \ldots, \hat{\beta}_K)' = \left[\sum_{i \in s} \frac{a_i \mathbf{x}_i \mathbf{x}_i'}{\sigma_i^2}\right]^{-1} \sum_{i \in s} \frac{a_i \mathbf{x}_i y_i}{\sigma_i^2}. \tag{2.3}$$

Even if model (2.1) fails to some degree, $\hat{y}_R$ will still have reasonable design-based properties because, even though the model assumptions motivate the estimator, $\hat{y}_R$ is design consistent irrespective of whether the assumed model is true or false. This is clear from (2.2). If $\hat{y}_\pi$ and $\hat{\mathbf{x}}_\pi$ are design consistent estimators of Y, the population total of y, and of $\mathbf{X}$, then the second term in $\hat{y}_R$ converges to zero while the first converges to Y. For more details, see Särndal, Swensson and Wretman (1992).

The regression estimator $\hat{y}_R$ can also be expressed as a weighted sum of the sample y_i's with i th weight,

$$w_i = a_i\left[1 + (\mathbf{X} - \hat{\mathbf{x}}_\pi)'\left(\sum_{i \in s} \frac{a_i \mathbf{x}_i \mathbf{x}_i'}{\sigma_i^2}\right)^{-1} \frac{\mathbf{x}_i}{\sigma_i^2}\right]. \tag{2.4}$$

From (2.4) it is easily seen that the known population totals are exactly reproduced for the auxiliary variables.

The estimator of $\boldsymbol{\beta}$ in (2.3) does not account for any correlation among the errors in model (2.1). In clustered populations, units that are geographically near each other, e.g., CU's in the same neighborhood, may be correlated. Using a full covariance matrix $\mathbf{V}$ may be more nearly optimal (e.g., see Casady and Valliant 1993 and Rao 1992). Though use of a full covariance matrix $\mathbf{V}$ may lower the variance of $\hat{\boldsymbol{\beta}}$, the elements of $\mathbf{V}$ will depend on the particular y being studied, and estimation of $\mathbf{V}$ is generally a nuisance. Consequently, it is interesting and practical to consider the simple case of $\mathbf{V} = \mathrm{diag}(\sigma_i^2)$ that leads to (2.2). Note that when the design-variance $\mathrm{var}_p(\hat{y}_R)$ is estimated, it will be necessary to use a method that properly reflects clustering and other design complexities.

The regression estimator has the disadvantage that the weights can be unreasonably large, small or even negative. The calibration estimators of Deville and Särndal (1992), introduced next, add constraints to restrict the size of the weights. Calibration estimators are formed by minimizing a given distance, F, between some initial weight and the final weight, subject to constraints. The constraints can involve the available auxiliary variables thus incorporating them into the estimator. The regression estimator presented above is a special case of the calibration estimator in which F is defined to be the generalized least squares (GLS) distance function, $F(w_i, a_i) = a_i c_i (w_i / a_i - 1)^2 / 2$ for $i = 1, \ldots, n$, with c_i a known, positive weight (e.g., $c_i = \sigma_i^2$ or $c_i = 1$) associated with unit i, and w_i, the final weight. The total sample distance $\sum_{i \in s} F(w_i, a_i)$ is minimized subject to the constraints, $\sum_{i \in s} w_i \mathbf{x}_i = \mathbf{X}$. In this form, the weights of the regression estimator of the population total of y given in (2.4) can be written as,

$$w_i = a_i g(c_i^{-1} \boldsymbol{\lambda}' \mathbf{x}_i) \tag{2.5}$$

for $i = 1, \ldots, n$ where

$$g(u) = 1 + u, \tag{2.6}$$

for $u \in \Re$ and $\boldsymbol{\lambda}$ is a Lagrange multiplier evaluated in the minimization process. The calibration weights can refine the unreasonably extreme values resulting in (2.5) by restricting g so that

$$g(u) = \begin{cases} L & \text{if } u < L - 1 \\ 1 + u & \text{if } L - 1 \le u \le U - 1. \\ U & \text{if } u > U - 1 \end{cases} \tag{2.7}$$

With this definition of g, the weights w_i satisfy, $L < w_i / a_i < U$, for $i = 1, \ldots, n$ so that L and U can be chosen in such a way as to reflect the desired restrictions on the weights. Choosing $L>0$ ensures that the weights are positive, and U is picked to be appropriately small to prohibit large weights. The calibration weights must be solved for iteratively; one easily programmed algorithm is given in Stukel and Boyer (1992).

In most household surveys, post-stratification serves primarily as an adjustment for undercoverage of the target population by the frame and the sample. In the U.S., there are no reliable population counts of households to use in post-stratification. Consequently, population counts of persons are used for the post-strata control totals. This disagreement in the unit of analysis (the household) and the unit of post-stratification (the person) when a household characteristic is of interest led to the development of the PP method that is used in the CE and Current Population Surveys.

In the PP method described in Alexander (1987), a household begins the weighting process with a single base weight, a_i, that is then adjusted for nonresponse. The adjusted weight is assigned to each person in the household and the person weights are then further adjusted to force them to sum to known population controls of persons by age, race, and sex. This last adjustment can result in persons having different weights within the same household. The household is then assigned the weight of the person designated as the "principal person" in the household. This method has an element of arbitrariness and is difficult to analyze mathematically. The regression and calibration estimators can be formulated in such a way that population person controls are satisfied, all persons in a household retain the same weight, and no arbitrary choice among person weights is needed to assign a household weight.

3. AN APPLICATION

We compare the three estimators (i.e., regression, restricted calibration (with $L=.5$, $U=4$), and principal person) by an application to the estimated means and their estimated standard errors for a number of expenditures from the CE Survey sponsored by the Bureau of Labor Statistics.

The CE Survey gathers information on the spending patterns and living costs of the American consumers. There are two parts to the survey, a quarterly interview and a weekly diary survey. The Interview Survey collects detailed data on the types of expenditures which respondents can be expected to recall for a period of three months or longer (e.g., property, automobiles, major appliances)—an estimated sixty to seventy percent of total household expenditures. The sample is selected in two stages with geographic primary sampling units at the first stage and households at the second.

We evaluated the estimators described above for a number of expenditures from the Interview Survey. Data collected during the second quarter of 1992 consisting of $n=5156$ CU's were used. The CE Survey's primary unit of analysis is the consumer unit, an economic family within a household. A consumer unit (CU) consists of individuals in the household who share expenditures. Thus, there may be more than one CU in a household.

Five different sets of auxiliary variables were studied. They were chosen by testing the adequacy of model (2.1) for the selected expenditures with different combinations of the available auxiliary variables. The 56 post-strata based on age/race/sex currently in use in the CE were included. The combinations of auxiliaries used to form the different weights are given in Table 1. The number of auxiliary variables in each model is given within parentheses. Based on this information, weights (2.5) were computed using g given in (2.6)—regwts—and (2.7)—calwts. For both the regression and restricted calibration weights, we set a_i equal to the adjusted base weight, i.e., $1/\pi_i$ times a nonresponse adjustment.

Table 1. Weights and their corresponding auxiliary variables. Number of cells are in parantheses.

Weight	Auxiliary Variables
regwts0	age/race/sex (56)
regwts1	inter., age/race/sex, region, urban×region (18)
regwts2	intercept, age/race/sex, region, urban×region, age of reference person, housing tenure, family income before taxes (24)
calwts0	age/race/sex (45)
calwts1	inter., age/race/sex, region, urban×region (18)
calwts2	intercept, age/race/sex, region, urban×region, age of reference person, housing tenure, family income before taxes (24)
calwts3	intercept, age/race/sex, region, urban×region, family income before taxes (truncated at $500,000) (19)
calwts4	intercept, age/race/sex, region, urban×region, age of reference person, housing tenure (23)
PP	age/race/sex (56)

For this application, the population totals necessary to evaluate $\mathbf{X}=(X_1,\ldots,X_K)'$ were obtained mostly from the 1990 Census figures projected to 1992 and the Current Population Reports published by the U.S. Bureau of the Census.

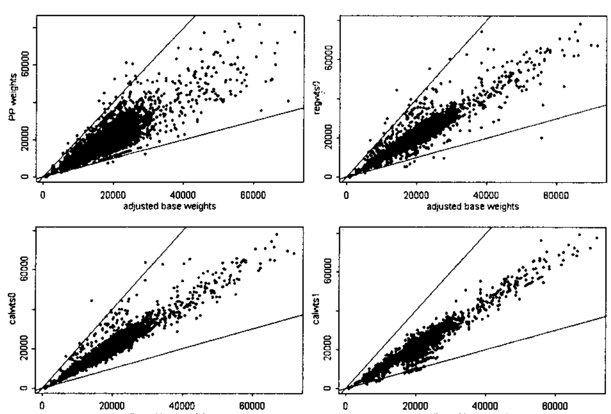
3.1 Comparisons of Weights and Estimated CU Counts

Although the means and standard errors of survey estimates are the key statistics for comparing weighting methods, the weights themselves have sufficiently differing properties to be worth mentioning. An important difference between the regwts and the calwts is the potential for the former to be negative.

Both regwts1 and regwts2 had only 1 negative weight each out of the 5156 weights. However, of the 44 sets of replicate weights, nearly half the sets for each of regwts0, regwts1 and regwts2 had some negative weights though the maximum number of negative weights for any replicate was 3. The negatives are a potential cause of inflated standard errors, since the negative weights will be offset by large positive weights in order for the fixed population control totals to be met in every replicate. Calwts, which restrict the deviation from the base weights by choosing L and U appropriately, (in this instance, L=0.5 > 0) naturally did not produce any negative weights.

On examining scatter plots (not shown here) comparing some of the different weights to each other, the PP and regwts0, while being substantially different from each other, exhibited final weights that can be considerably different from the adjusted base weights. The adjustments can be either up or down. A less variable set of adjustments was apparent in regwts1, calwts0, and calwts1. Calwts1 and calwts4 were quite similar and both were close to regwts1. The two sets of weights that involve the quantitative variable family income before taxes, calwts2 and calwts3, were closely related. Some CU's had calwts2 values larger than 60,000 but had calwts0, calwts1, calwts4 < 30,000. These CU's all had family incomes before taxes of a quarter of a million dollars or more. Thus, the inclusion of that variable in the calibrations did have a substantial impact on some units. We did use a control only on the grand total income; having controls by income classes might have changed the weights on some of these cases.

Figure 1. Four sets of weights plotted against adjusted base weights. Reference lines correspond to L=.5 and U=2.



Picking $U = 2$ or 3 rather than 4 had little effect on the calwts. Figure 1 shows plots of the PP weights, regwts0, calwts0, and calwts1 versus the adjusted base weights. Even though that $a_i / 2 < w_i < 4a_i$ for each i for the calwts, the lower right panel in Figure 3 shows that calwts1 satisfy $a_i / 2 \le w_i \le 2a_i$, for each i. The upper two panels indicate that the PP weights and regwts0 do not conform to the restriction $a_i / 2 \le w_i \le 2a_i$.

Previous studies at BLS regarding generalized regression estimation in the CE had concluded that the number of single person CU's was under estimated, at least compared to the estimate produced by the PP method. We found minimal evidence of that phenomenon here. This is indicated by the ratios shown in Table 2. It contains the ratio of the estimated number of CU's under the alternative procedures to that of the PP estimation procedure, by size of CU.

Table 2. Estimated counts in thousands of CU's by CU size for PP weights and ratios of other estimated counts to the PP weights estimates. Ratios greater than 1.02 and less than 0.98 are highlighted.

Weights	CU Size				
	1	2	3	4	5+
PP	28,784	30,680	15,409	15,068	9,993
regwts0	0.96	0.99	1.01	0.99	1.02
regwts1	1.00	1.00	1.02	0.98	0.99
regwts2	1.00	1.01	1.01	1.01	0.97
calwts0	0.96	0.99	1.00	1.00	1.02
calwts1	1.00	1.00	1.02	0.98	0.99
calwts2	0.99	1.01	1.01	1.00	0.97
calwts3	0.98	1.02	1.01	1.01	0.96
calwts4	1.01	1.00	1.01	0.99	0.99

A similar table constructed by Composition of CU showed that while regwts0 and calwts0 estimators were substantially different from PP for the category One parent: 1+ children, for single person CUs they were not.

3.2 Precision of Estimates from the Different Methods

Although comparison of weights is instructive, the methods must ultimately be judged based on the level of estimated CU means and their precision. The standard errors of these estimators were computed via the method of balanced half sampling (BHS) using 44 replicates as currently implemented in the CE for the PP estimator. The BHS estimator is constructed to reflect the stratification and the clustering that is used in the CE. As the expenditure estimates from the CE Survey are published for various domains of interest, we computed the means and the standard errors for a few chosen domains as well. For each of these, the coefficient of variation (cv) was computed and then its ratio to the cv of the PP estimate was calculated.

For each type of weight, if the ratio of each expenditure cv to that of the PP weights is less than one, an improvement over the PP estimate is indicated since, for all the weights, the expenditure mean estimates were very close to those of the PP estimates. We computed the ratios of cv's and the ratios of means for each of the sets of weights described in Table 1, for each of the chosen expenditures, and for each of the following domains: Age of Reference Person, Region, Size of CU, Composition of Household, Household Tenure, and Race of Reference Person.

Table 3. Ratios to CE cv to cv's for the different weighting methods. The minimum ratio is highlighted in each row.

Expenditure	regwts			calwts		
	0	1	2	0	1	2
All Exp.	0.98	0.90	0.79	0.98	0.90	0.78
Shelter	0.93	0.85	0.75	0.93	0.85	0.74
Utilities	1.08	1.03	0.94	1.07	1.03	0.88
Furniture	1.08	1.21	3.52	1.06	1.21	2.58
Maj. ap.	1.08	1.06	1.04	1.06	1.08	1.09
All vehi.	0.90	0.89	0.98	0.91	0.89	0.98
Cars, (n)	0.95	0.91	1.01	0.96	0.91	1.02
Cars, (u)	0.98	0.94	0.96	0.97	0.94	0.97
Gasol.,	1.17	1.11	1.03	1.12	1.10	0.99
Health	1.05	0.97	0.86	1.07	0.97	0.85
Educat.	0.92	0.93	1.04	0.91	0.93	1.06
Contrib.	1.01	1.02	1.28	1.01	1.02	1.30
Pers. Ins.	1.00	0.97	1.64	1.01	0.98	1.24
Life, Ins.	1.08	1.02	1.53	1.08	0.98	1.38
Pensions	1.00	0.99	1.75	1.01	0.99	1.34

In addition, ratios for all CU's, i.e., the total across the domains, were computed for each expenditure and those for regwts 0, 1, 2 and calwts 0, 1, 2 are shown in Table 3. For All Expenditures, regwts2 and calwts2 with ratios of .79 and .78 provide substantial reduction in cv compared to PP. For less aggregated expenditures, regwts1 or calwts1 provide reasonably consistent improvements over PP without the losses incurred by some of the other weights for expenditures like Furniture, Personal insurance and pensions, and its subcategory Pensions and social security.

A trellis plot (Cleveland 1993) of the cv and mean ratios for calwts0 and calwts1 by age of reference person is given in Figure 2. Calwts0 is pictured because it is the nearest calibration equivalent to the current method of post-stratification. Calwts1 appears to be the best of the alternatives we have examined in the sense of improving the All Expenditures estimates while providing consistent performance for individual expenditure groups. In each panel of the plot a vertical reference line is drawn at 1, the point of equality between the calibration results and those for the PP method. The lower tier in the plot presents ratios of means from calwts0 and calwts1 to the PP means and illustrates that with a few exceptions the levels of the means from the two calibration choices are about the same as from PP. Similar results were obtained in the other domains we examined as well. The two calibration choices, in the main, improve cv's compared to PP, i.e. cv ratios tend to be less than 1, for most domains and expenditures, and calwts1 is somewhat better than calwts0.

Calwts2 and calwts3, which used family income before taxes as one of the auxiliaries, had somewhat erratic performance for domains, sometimes making major improvements over PP but occasionally showing serious losses. This is connected to the nature of the family income variable which had a substantial number of CU's with negative and zero values. These CU's vitiate the usefulness of this variable in predicting expenditures.

Taking all of the above into consideration, regwts1, calwts1 and calwts4 can be deemed a clear improvement over the PP estimator. Calwts1 has the advantage of non-negative weights over regwts1. Since calwts4 requires 23 auxiliary variables as opposed to calwts1's 18, we recommend calwts1 over all the other types of weights we have considered.

4. CONCLUSION AND FUTURE RESEARCH

The objective of this study was to investigate alternatives to the principal person method for deriving household weights that did not depend on the weight of one single member of the household. Different types of weights based on the regression estimation procedure were presented and their relative merits evaluated. Regression estimation incorporates the current survey post-stratification methods in which the weighted sum of the persons in each post-stratum is forced to be equal to an independent census count of that number. This is accomplished via auxiliary variables that are incorporated into the regression model. It also automatically produces for each sample household a weight that does not depend on any single one of its members. In order to eliminate the undesirable negative weights that can result from ordinary least-squares regression estimation, calibration estimators were adapted to the present problem. The calibration estimation procedure has the flexibility to restrict the possible deviation of each final weight from its base weight while adhering to the properties discussed above. This in particular allows the constraint of positive weights. The calibration weights are easily computed via matrix-oriented software like S-Plus™.

Overall, the ordinary regression estimator and the calibration estimator both appeared to be an improvement over the Principal Person estimator in terms of the coefficient of variation. For the future, the calibration estimators can be further refined by using the properties of regression estimation to choose the auxiliary variables, and hence the post-strata, optimally in order to reduce the redundancy of information that gets incorporated into the survey estimation procedure.

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Figure 2. Ratios to CE of cv's and means for two weighting methods by age of reference person.