Adjusting for Nonresponse in the Healthcare Survey of DoD Beneficiaries

Nancy A. Clusen[1], Haixia Xu[1], and Michael Hartzell[2]
Mathematica Policy Research[1]
Department of Defense[2]

Abstract

This paper presents the findings of an investigation of alternative forms of weighting adjustments to compensate for nonresponse in the Health Care Survey of DoD Beneficiaries. Currently, we compensate for potential nonresponse bias by adjusting for nonresponse within weighting cells defined by the stratification variables: enrollment status, beneficiary group, and geographic area. However, a great deal more is known about both respondents and nonrespondents from the sample frame. The first stage of the research identified variables from the frame that were most related to response to the survey. Second, we incorporated the chosen auxiliary variables into a weighting adjustment procedure. Three alternative weighting adjustment procedures were used: (1) a response propensity model, (2) forming weighting cells by dividing the predicted response propensity scores distribution into equal, ordered subgroups, and (3) forming weighting cells according to predicted response propensity scores and multiple outcome variables. Lastly, we compared and evaluated the results of using the alternative weighting procedures and the current procedure.

Keywords: Unit Nonresponse Adjustment

1. Introduction

This paper presents the findings of an investigation of alternative forms of weighting adjustments to compensate for unit nonresponse in the Health Care Survey of DoD Beneficiaries (HCSDB), an ongoing quarterly survey conducted by the TRICARE Management Activity, Department of Defense. Unit nonresponse, which is the failure to collect the survey data for eligible beneficiaries, when not adjusted for, may result in bias in survey estimates. The weighting adjustments studied here aim to modify the weights of respondents to compensate for the nonrespondents.

Under the current HCSDB design, a stratified probability sample of all adults eligible for military health benefits is surveyed each quarter. The sample frame is the Defense Enrollment Eligibility Reporting System (DEERS). The investigation reported here was conducted with the data from Quarter 2 2004 survey. Of the 50,000 sampled beneficiaries, 71 percent failed to provide data, that is, they were nonrespondents. See Mathematica Policy Research (2003; 2004) for further information on the HCSDB design.

With the level of nonresponse experienced in the HCSDB and the likelihood that respondents and nonrespondents will differ in terms of their responses to survey questions, nonresponse bias is potentially serious. Moreover, since the HCSDB began in 1995 nonresponse has increased; therefore we are increasingly concerned about potential nonresponse bias. Currently, we compensate for potential nonresponse bias by adjusting for nonresponse independently within weighting classes defined by enrollment status, beneficiary group, and geographic area. With this method we assume that both response propensity and characteristics related to survey outcome variables are homogeneous within these classes.

Because the HCSDB sample is selected from the DEERS, a great deal is known about both respondents and nonrespondents. Therefore, a wide choice of variables is available for use as auxiliary variables in the nonresponse weighting adjustments. The auxiliary variables currently being used are the stratification variables, a small subset of those available.

The number of variables known for nonrespondents raises two issues for nonresponse weighting adjustments. First, there is the choice of which auxiliary variables from the many variables available from the frame are best to use in the weighting adjustment procedure. Second, there is the choice of a suitable weighting adjustment methodology to incorporate the chosen auxiliary variables. We investigate both of these issues in this research. The first stage of the research identified variables from the frame that were most related to whether or not a beneficiary responded to the survey. After initial screening of variables, the CHAID (Chi-squared Automatic Interaction Detection) (Biggs et al. 1991) technique was used for this purpose. Second, we incorporated the chosen auxiliary variables into a weighting adjustment procedure. Three alternative weighting adjustment procedures were used. Lastly, we compared and evaluated the results of using the alternative weighting procedures and the current procedure.

2. Literature Review

It is common practice to use weighting adjustment to compensate for unit nonresponse in sample surveys. There are numerous methods developed to make these adjustments (Kalton and Maligalig 1991; Holt and Smith 1979; Oh and Scheuren 1983; Little and Vartivarian 2003; Vartivarian and Little 2003). Moreover, a number of studies have evaluated multiple weighting methods to adjust for nonresponse. Carlson and Williams (2001) found nearly identical results for weighting classes using the design features (strata and sampling units) and propensity models containing numerous variables identified as predictors of response. However for key geographic domains they did see some gains from the response propensity models. Rizzo *et al.* (1994) investigated several alternative methods for panel nonresponse in the Survey of Income and Program Participation, including nonresponse adjustment cells, logistic regression, CHAID methods, and generalized raking methods. They found a number of variables related to panel nonresponse that are not employed in the standard SIPP nonresponse adjustment cells methodology. These variables were used in the alternative weighting methods and were found to result in similar weights regardless of method. Therefore, Rizzo *et al* conclude that the choice of model variables is more important than the weighting methodology.

3. Current Nonresponse Weight Adjustments

Currently, we compensate for potential nonresponse bias by adjusting for nonresponse independently within weighting classes (Mathematica Policy Research 2003). Weighting class adjustments are made by partitioning the sample into groups, called weighting classes, and then adjusting the weights of respondents within each class so that they sum to the weight total for nonrespondents and respondents from that class. Implicit in the weighting class adjustment is the assumption that—had the nonrespondents responded—their responses would have been distributed in the same way as the responses of the other respondents in their weighting class. The 2004 Adult HCSDB weighting classes are defined on the basis of the stratification variables: TRICARE Prime enrollment status, beneficiary group, and geographic area. Moreover, we make two separate weighting adjustments to attempt to compensate for nonresponse, because eligibility determination and cooperation have distinct response patterns (Iannacchione 2003). First, we adjust the sampling weights to account for sampled beneficiaries for whom eligibility status could not be determined. Second, we adjust for incomplete or missing questionnaires from beneficiaries known to be eligible.

4. Predictors of Response Propensity

The first step in developing nonresponse adjustments is deciding which of the large number of variables available from the HCSDB sample frame would be best to use in the adjustment procedures. We do this by evaluating each variable and its relationship to response. Segmentation analysis using the CHAID software was used to allow for a model-building process that focuses on segments showing different response propensities. This analysis also avoids the problem of examining "all possible interactions" that is typical of regression modeling. The unweighted segmentation algorithm split the sample into subgroups based on response rates. The splitting process continued until either no other predictors were found or the segment size fell below a minimum size. For ease of interpretation, we also limited the splitting process to three levels. Furthermore, the CHAID analysis was run twice, once to predict eligibility determination and again to predict survey completion among eligible beneficiaries. We used these segments, along with the corresponding main effects, in the logistic regression models developed for use in the nonresponse weighting adjustments.

5. Alternative Nonresponse Weight Adjustments

5.1 Response Propensity

The first alternative weighting method is a response propensity model. The method uses a model of the relationship between a set of beneficiary characteristics and a response outcome. We use logistic regression to model this relationship because response outcome is dichotomous: beneficiaries either respond or they do not. If the characteristics in the model predict response well and if the characteristics are correlated with the substantive variables of the survey, then the model-based adjustment factors applied to the sampling weights greatly reduce the potential for nonresponse bias. Like the current weighting class adjustment method, we make two separate weighting adjustments to attempt to compensate for nonresponse: an eligibility determination adjustment and a completion adjustment.

The overall probability of determining eligibility is estimated with the logistic regression model. The probability that sample beneficiary i has eligibility status determined is:

$$\begin{aligned}\hat{\lambda}_i &= P\left[E_i = 1 \mid X_i\hat{\beta}\right] \\ &= \left[1+\exp\left(-X_i\hat{\beta}\right)\right]^{-1}\end{aligned} \tag{1}$$

where

$$E_i = \begin{cases}1 \text{ if sample beneficiary } i \text{ has eligibility status determined} \\ 0 \text{ otherwise}\end{cases}$$

and X_i is a vector of HCSDB response predictors (main effects and interaction terms).

To determine the set of response predictors we used an unweighted stepwise logistic regression procedure in SAS. We developed a model for each TNEX region (North, South, West, and Outside of Continental U.S.) and included as response predictors an indicator variable for each catchment area in the appropriate TNEX region. Because catchment areas are an important stratification variable, we included all corresponding catchment areas in the model for each TNEX region, regardless of significance. In addition to catchment areas, we included all variables and interactions identified by the CHAID analysis as response predictors. The SAS stepwise procedure worked iteratively adding and subtracting variables from the model until each remaining coefficients for each variable met the precision requirements, p = 0.15. All catchment area variables remained in the model regardless of the significance of their coefficients.

The variables in the resulting SAS model were used as a starting point for the models estimated using SUDAAN. We estimated the coefficients using a weighted logistic regression procedure, which also incorporates the stratified design in estimating standard errors for the coefficients. Again, we reduced the model until each remaining coefficient met the precision requirement described above.

Therefore, the eligibility determination adjustment factor for beneficiary i is:

$$ADJ_i^E = \begin{cases}\hat{\lambda}_i^{-1} & \text{if } E_i = 1 \\ 0 & \text{if } E_i = 0\end{cases} \tag{2}$$

The adjustment ADJ^E was then applied to the sampling weights W_i to obtain the eligibility-status adjusted weight for sample beneficiary i:

$$W_i^E = W_i \times ADJ_i^E \tag{3}$$

We repeat the same process used in developing the eligibility determination factor to develop the completion adjustment factor. We used stepwise logistic regression in SAS for each TNEX region, included all variables and interactions identified by the CHAID analysis as response predictors, and did not include the catchment areas. The overall probability of completion is estimated with a weighted logistic regression model estimated in SUDAAN using the eligibility-status adjusted weight calculated in the previous step. For the Outside of Continental U.S. (OCONUS) model, we did not find any significant predictors of completion.

The probability that sample beneficiary i completed the survey is:

$$\begin{aligned}\hat{\rho}_i &= P\left[R_i = 1 \mid X_i\hat{\beta}\right] \\ &= \left[1+\exp\left(-X_i\hat{\beta}\right)\right]^{-1}\end{aligned} \tag{4}$$

where

$$R_i = \begin{cases}1 \text{ if sample beneficiary } i \text{ has completed a survey} \\ 0 \text{ otherwise}\end{cases}$$

and X_i is a vector of HCSDB response predictors (main effects and interaction terms). The resulting completion adjusted weight for beneficiary i is:

$$ADJ_i^C = \begin{cases}\hat{\rho}_i^{-1} & \text{if } \mathrm{R}_i = 1 \\ 0 & \text{if } \mathrm{R}_i = 0\end{cases} \tag{5}$$

Because we found no predictors of completion for the OCONUS region, the adjustment factor ADJ^C is 1 for all OCONUS beneficiaries completing a survey.

The questionnaire-completion adjusted weight W^C is calculated as the product of the questionnaire-completion adjustment ADJ^C and the eligibility-status adjusted weight W^E or:

$$W_i^C = W_i^E \times ADJ_i^C \tag{6}$$

Lastly, the nonresponse-adjusted weights are poststratified to the frame totals to obtain weighted totals equal to population totals. Moreover, important analytic domains for which weighted totals should equal population totals define the poststrata. The poststrata are defined by stratification variables, enrollment status, beneficiary group, and geographic area, and are collapsed to form poststrata of sufficient size. The poststratification adjustment factor for the h^{th} poststratum is defined as:

$$(7) \qquad A_h^{PS} = \frac{N_h}{\sum_{i \in h} W_i^C}$$

where N_h is the total number of beneficiaries in the DEERS frame associated with the h^{th} poststratum. The poststratified adjusted weight for the i^{th} respondent from the h^{th} poststratum is then calculated as:

$$(8) \qquad W_{hi}^{PS} = A_h^{PS} \times W_i^C$$

When summed over respondents in poststratum h, the poststratified weights now total N_h. Moreover, when summed over all respondents, the sum of the poststratified adjusted weights is equal to the total population.

5.2 Response Propensity Weighting Classes

The second alternative approach for nonresponse adjustments involved developing weighting classes using design characteristics and the response propensity model developed in the first method. The usual HCSDB approach computes the response weight adjustment cells based on fully observed variables from the sample frame. However, in order to avoid empty or sparsely populated cells, we limited our classification to the sample design variables, catchment area, enrollment, and beneficiary group, and collapse these cells as necessary.

The alternative approach we used to reduce the number of cells was to stratify based on response propensity. Similar to the first alternative weighting method above, the second technique used a logistic regression model to predict response. Stratifying using the response propensity score for each sampled beneficiary, we developed a manageable number of weighting class cells. The nonresponse adjustment was calculated within each weighting class as the inverse of the response rate within the class.

Thus, the second alternative weighting method starts with the use of the two response propensity models developed for the first alternative method: an eligibility determination model and a completion model. For each eligibility determination model for a given region, we ordered the list of response propensity scores and then divided them into groups of equal size. We created a total of 40 weighting classes, 10 for each region. The eligibility determination adjustment factor for the c^{th} weighting class is defined as:

(9)

$$A_c^E = \frac{\sum_{i \in c} W_i}{\sum_{i \in c} \delta_E W_i} \text{ beneficiaries eligibility status determined}$$

$$= 0 \text{ otherwise}$$

where W_i is the sample weight and δ_E is equal to 1 for beneficiaries whose eligibility status was determined and 0 otherwise. The eligibility determination adjusted weight for the i^{th} sample record from the c^{th} weighting class is then calculated as:

$$(10) \quad W_{ci}^E = A_c^E \times W_i$$

For each completion model for a given region, we ordered the list of response propensity scores and then divided them into groups of equal size. We created a total of 29 weighting classes, 10 for the North, 8 for the South, 10 for the West, and one for Outside of Continental U.S. The completion adjustment factor for the d^{th} weighting class is defined as:

$$A_d^C = \frac{\sum_{i \in d} W_i^E}{\sum_{i \in d} \delta_C W_i^E} \text{ for eligible beneficiaries}$$

$$(11) \qquad = 1 \text{ for ineligible beneficiaries}$$

$$= 0 \text{ otherwise}$$

where W^E is the eligibility determination adjusted weight and δ_C is equal to 1 for beneficiaries who completed the survey and 0 otherwise. The completion adjusted weight for the i^{th} respondent in the d^{th} weighting class was then calculated as:

$$(12) \quad W_{dci}^C = A_d^C \times W_{ci}^E$$

Lastly, the nonresponse-adjusted weights were poststratified to the frame totals to obtain weighted totals equal to population totals. The poststrata were defined by stratification variables, enrollment status, beneficiary group, and geographic area, and were collapsed to form poststrata of sufficient size. The poststratification adjustment factor for the h^{th} poststratum is defined as:

$$(13)\quad A_h^{PS} = \frac{N_h}{\sum_{i \in h} W_{dci}^{C}}$$

where N_h is the total number of beneficiaries in the DEERS frame associated with the h^{th} poststratum. The poststratified adjusted weight for the i^{th} sample record from the h^{th} poststratum is then calculated as:

$$(14)\quad W_{hdci}^{PS} = A_h^{PS} \times W_{dci}^{C}$$

Therefore, when summed over all respondents in poststratum h, the poststratified weights now total N_h.

5.3 Response Propensity and Predictive Mean of Survey Responses Weighting Classes

The third alternative approach for nonresponse adjustments also involved developing weighting classes using design characteristics and the response propensity model as well as survey responses. The efficiency and robustness of weighting adjustments may be increased if the weighting classes are based on two variables: the response propensity and the predictive mean of survey responses. If we simply used the predictive mean response, then each survey estimate would use a different set of weights, an undesirable result. Therefore, we investigated this method using weighting classes based on response propensity and the predictive mean of a single canonical outcome variable, where that canonical outcome variable is calculated from several survey variables. This method allows for multiple key survey variables to inform the weighting class cell formation, with one set of resulting analysis weights.

The third alternative weighting method starts with the use of the two response propensity models developed for the first and second alternative methods. In addition, we calculated the canonical outcome variable from several key survey variables, which measure access to, use of, and satisfaction with the military health system. We then formed weighting classes based on the cross classification of response propensity and the predictive mean of a single canonical outcome variable. The eligibility determination adjustment factor for the f^{th} weighting class is defined as:

(15)

$$A_f^{E} = \frac{\sum_{i \in f} W_i}{\sum_{i \in f} \delta_E W_i} \text{ beneficiaries eligibility status determined}$$

$$= 0 \text{ otherwise}$$

where W_i is the sample weight and δ_E is equal to 1 for beneficiaries whose eligibility status was determined and 0 otherwise. The eligibility determination adjusted weight for the i^{th} sample record from the f^{th} weighting class is then calculated as:

$$(16)\quad W_{fi}^{E} = A_f^{E} \times W_i$$

For each completion model for a given region, we ordered the list of response propensity scores and then divided them into groups of equal size. The completion adjustment factor for the g^{th} weighting class is defined as:

$$A_g^{C} = \frac{\sum_{i \in g} W_i^{E}}{\sum_{i \in g} \delta_C W_i^{E}} \text{ for eligible beneficiaries}$$

$$(17)\qquad = 1 \text{ for ineligible beneficiaries}$$

$$= 0 \text{ otherwise}$$

where W^E is the eligibility determination adjusted weight and δ_C is equal to 1 for beneficiaries who completed the survey and 0 otherwise. The completion adjusted weight for the i^{th} respondent in the g^{th} weighting class was then calculated as:

$$(18)\quad W_{gfi}^{C} = A_g^{C} \times W_{fi}^{E}$$

Lastly, the nonresponse-adjusted weights were poststratified to the frame totals to obtain weighted totals equal to population totals. The poststrata were defined by stratification variables, enrollment status, beneficiary group, and geographic area, and were collapsed to form poststrata of sufficient size. The poststratification adjustment factor for the h^{th} poststratum is defined as:

(19) $A_h^{PS} = \frac{N_h}{\sum_{i \in h} W_{dci}^C}$

where N_h is the total number of beneficiaries in the DEERS frame associated with the h^{th} poststratum. The poststratified adjusted weight for the i^{th} sample record from the h^{th} poststratum is then calculated as:

(20) $W_{hgfi}^{PS} = A_h^{PS} \times W_{gfi}^C$

Therefore, when summed over all respondents in poststratum h, the poststratified weights now total N_h.

6. Comparison of Survey Estimates Using Alternative Weighting Procedures

Given the methods described above for adjusting sampling weights using additional respondent characteristics, we compare each method to determine the best technique for improving the accuracy of statistics calculated from the HCSDB. We compare estimates calculated using SUDAAN for key statistics under each weighting scheme and their corresponding variance estimates calculated using a Taylor series linearization method. Key statistics were determined in consultation with the TRICARE Management Activity, and include smoking prevalence, health plan and care ratings, and other items.

We calculated these estimates for all beneficiaries, and then for a number of important subgroups as well: active duty beneficiaries, active duty family members, retirees younger than 65 years old, retirees over 65, and all enrollees. In general, the estimates are similar for the current method, and the three alternative methods, especially when looking at the total population. This is true for most subgroup estimates as well. However, within key subgroups, the standard errors for many estimates are larger under the two new weighting adjustment methods than under the current method. See tables 1 and 2 for some results.

6.1 Differences in Estimates

There are some important differences in subgroup estimates. The estimated proportion reporting no problem getting a doctor or nurse they are happy with is higher under the three new weighting adjustment methods for active duty beneficiaries (57 percent versus 54 percent). The estimated proportion of smokers is higher under the two new weighting adjustment methods for active duty beneficiaries (27 percent versus 23 percent), active duty family members (19 percent versus 16 percent), and enrollees (23 percent versus 20 percent). There is no difference across methods in the estimated proportion of smokers for retirees less than 65 or retirees over 65.

The estimated proportion that knows their blood pressure is lower under the two new weighting adjustment methods for active duty beneficiaries (87 percent versus 90 percent), active duty family members (87 percent versus 89 percent), retirees younger than 65 (91 percent versus 93 percent), and enrollees (88 percent versus 91 percent). There is no difference across methods in the estimated proportion of retirees over 65 who know their blood pressure.

Lastly, the estimated proportion of pregnant women receiving prenatal care in the first trimester is lower under the three alternative methods for active duty beneficiaries (80 percent versus 82, 81, and 81 percent) than the other methods.

6.2 Differences in Standard Error Estimates

There are also some important differences in the estimated standard errors for these key estimates. For the total population, the estimated standard errors are nearly the same for the current method, the response propensity method, and the response propensity weighting class method. However for some subgroups, active duty beneficiaries, active duty family members, and retirees less than 65, the differences in standard errors are larger under the alternative methods.

For active duty beneficiaries, the standard errors for all estimates are larger under the three alternative methods. The increase in the standard error ranges from 4 to 67 percent. The largest standard error increase is for the proportion that knows their blood pressure (67 percent greater) and the smallest standard error increase is for the proportion of pregnant women receiving prenatal care in the first trimester (4 to 9 percent greater).

For active duty family members, the standard errors are very similar across the three methods. The increase in the standard errors ranges from 0 to 25 percent. The largest standard error increase is for the proportion that knows their blood pressure (25 percent greater). The smallest standard error increase is for the proportion rating their health plan an 8 or higher; the standard errors are equal across the methods.

For retirees less than 65, the standard errors are somewhat higher for the two alternative methods. The increase in the standard errors ranges from 0 to 40 percent. The largest standard error increase is for the proportion that knows their blood pressure (40 percent greater). The smallest increase is for the proportion rating their personal doctor or nurses an 8 or higher; the standard errors are equal for all methods.

7. Discussion

These analyses have identified a number of frame variables that are related to nonresponse and that are not employed in the current nonresponse adjustments. These include age, sex, marital status, personnel category, rank, and the interactions among these variables. These and other variables were included as auxiliary variables in developing weights for the HCSDB using the three alternative weighting methods. The response propensity method, the response propensity weighting class method, and the response propensity and predictive mean weighting class method produced estimates similar to the current method, for most items.

It is significant that most of the key estimates are not different from the current weighting method. These key variables seem unaffected by the additional explanatory variables used in the three new methods. However, a lack of differences in estimates, on their own, does not indicate less bias. To measure bias we need a source of data with higher accuracy than our survey data. The 2002 Survey of Health Related Behaviors Among Military Personnel could be considered more accurate because the survey is multi-mode (administered on-site at large installations and by mail elsewhere) and achieves a higher response rate than the HCSDB (55.6 percent versus 29 percent). One common measure between the HCDSB and the Health Related Behaviors survey is the proportion of smokers among active duty beneficiaries. The Health Related Behaviors survey estimates higher rates of smokers among active duty beneficiaries, 33.8 percent in 2002 (standard error 1.3), as compared to 23 percent (standard error 0.9) for the HCSDB under the current weighting method. The new methods estimate smoking rates of 27 percent (standard error 1.2) among active duty beneficiaries. Therefore, the results of the three new methods may indicate that the current estimate is too low and that the higher rates of smoking estimated from the two new methods are less biased.

Decreasing bias often corresponds to an increase in variance. As may be expected, the three alternative methods lead to larger standard errors. The increase in variability is due to the increase in the variation of the adjustment factors for nonresponse. As can be seen in Table 2 the range of the nonresponse adjustments for the two new methods, which include poststratification, is much larger than the current weighting cell adjustment method. The largest adjustment for the response propensity model is nearly 3.5 times the maximum for the current weighting classes method, the largest adjustment for the response propensity weighting classes method is nearly 3 times the maximum for the current weighting classes method, and the largest adjustment for the response propensity and predictive mean weighting class method is 2 times the maximum for the current method.

Therefore, we conclude that the method used is not as important as the variables used to model nonresponse. In this case, the additional variables might reduce bias, but the three alternative methods that use these variables are similar in their results. This result is in line with the results of previous research by Carlson and Williams and Rizzo, Kalton, Brick, and Petroni.

References

Biggs, D., B. de Ville, and E. Suen. "A Method of Choosing Multiway Partitions for Classification and Decision Trees." *Journal of Applied Statistics*, vol. 18, 1991, pp. 49-62.

Carlson, Barbara Lepidus and Stephen Williams. "A Comparison of Two Methods to Adjust Weights for Non-response: Propensity Modeling and Weighting Class Adjustments." *2001 Proceedings of the American Statistical Association, Survey Research Methods Section* [CD-ROM]. Alexandria, VA: American Statistical Association.

Holt, D. and T.M.F. Smith "Post Stratification." *Journal of the Royal Statistical Society*, A, 142, pp. 33-46.

Iannacchione, Vincent G. "Sequential Weight Adjustments for Location and Cooperation Propensity for the 1995 Survey of Family Growth." *Journal of Official Statistics*, vol. 19, no. 1, 2003, pp. 31-43.

Kalton, Graham and Dalisay S. Maligalig. "A Comparison of Methods of Weighting Adjustments for Nonresponse." *1991 Annual Research Conference March 17-20, 1991*, pp. 409-428.

Little, Roderick J. and Sonya Vartivarian. "On Weighting the Rates in Non-response Weights." *Statistics in Medicine*, vol. 22, 2003, pp. 1589-1599.

Mathematica Policy Research "2003 Health Care Survey of DoD Beneficiaries: Adult Technical Manual." Submitted to TRICARE Management Activity, 2004.

Mathematica Policy Research "2004 Health Care Survey of DoD Beneficiaries: Adult Sampling Report." Submitted to TRICARE Management Activity, 2003.

Oh, H.L. and Fritz Scheuren. "Weighting Adjustments for Unit Nonresponse." In *Incomplete Data in Sample Surveys, vol. 2: Theory and Bibliographies*, edited by W.G. Madow, I. Olkin, and D. Rubin. New York: Academic Press, 1983.

Rizzo, Lou, Graham Kalton, Mike Brick, and Rita Petroni. "Adjusting for Panel Nonersponse in the Survey of Income and Program Participation." *1994 Proceedings of the American Statistical Association, Survey Research Methods Section*. Alexandria, VA: American Statistical Association.

Vartivarian, Sonya and Roderick J. Little. "Weighting Adjustments for Unit Nonresponse with Multiple Outcome Variables." *2003 Proceedings of the American Statistical Association, Survey Research Methods Section* [CD-ROM]. Alexandria, VA: American Statistical Association

TABLE 1 ESTIMATED PROPORTIONS FOR TOTAL POPULATION WITH ALTERNATIVE WEIGHTING METHODS

Variable	Current Weighting Classes	Response Propensity Model	Response Propensity Weighting Classes	Weighting Classes	Sample Size
Personal doctor or nurse rating[1]	0.77 (0.006)	0.77 (0.006)	0.77 (0.006)	0.77 (0.006)	8,169
Satisfied with doctor or nurse	0.63 (0.006)	0.63 (0.006)	0.64 (0.006)	0.64 (0.006)	12,355
No problem getting care	0.81 (0.005)	0.81 (0.005)	0.81 (0.005)	0.81 (0.005)	10,033
Blood pressure checked in last 2 yrs	0.92 (0.003)	0.91 (0.004)	0.91 (0.004)	0.91 (0.004)	14,063
Prenatal care received 1st trimester	0.90 (0.015)	0.90 (0.016)	0.90 (0.015)	0.90 (0.015)	619
Smokers	0.19 (0.004)	0.20 (0.005)	0.20 (0.005)	0.20 (0.005)	13,863

TABLE 2 ESTIMATED PROPORTIONS FOR ACTIVE DUTY BENEFICIARIES WITH ALTERNATIVE WEIGHTING METHODS

Variable	Current Weighting Classes	Response Propensity Model	Response Propensity Weighting Classes	Weighting Classes	Sample Size
Personal doctor or nurse rating[1]	0.65 (0.018)	0.65 (0.021)	0.65 (0.021)	0.65 (0.021)	1,525
Satisfied with doctor or nurse	0.54 (0.011)	0.57 (0.013)	0.57 (0.013)	0.57 (0.013)	4,196
No problem getting care	0.68 (0.012)	0.68 (0.014)	0.68 (0.015)	0.68 (0.015)	2,704
Blood pressure checked in last 2 yrs	0.90 (0.006)	0.87 (0.010)	0.87 (0.010)	0.86 (0.010)	4,393
Prenatal care received 1st trimester	0.82 (0.046)	0.80 (0.050)	0.81 (0.048)	0.82 (0.047)	118
Smokers	0.23 (0.009)	0.27 (0.012)	0.27 (0.012)	0.27 (0.012)	4,323

Note: standard errors are in parentheses [1]Rating 8 or higher on a scale of 0 to 10