Adjustments for Misclassification of Deployment Status in a Population Based Health Study of Operation Enduring Freedom and Operation Iraqi Freedom Veterans

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Abstract
In large, complex sample surveys, post-stratification techniques are generally used to address misalignment between the distributions in the survey data versus those in the population due to nonresponse and "frame coverage" problems. When the administrative data used to construct the survey frame contains information that does not match the self-reported information (misclassification), post-stratification may not fully correct any misalignments. To account for misclassification in the sampling variable, we propose a technique that Kuha and Skinner (1997) used to adjust survey estimates. We used this method in the National Health Study for a New Generation of U.S. Veterans (NewGen) to adjust the control totals used as benchmarks in post-stratification. We were able to adjust the weighting when a primary sampling and analysis variable, deployment status, contains misclassification. This variable indicates whether a veteran had served in a combat theater in Operation Enduring Freedom or Operation Iraqi Freedom. Without accounting for misclassification, weighted survey estimates are potentially biased, especially for analysis involving misclassified deployment status. We performed raking when the benchmarked population counts were corrected from misclassification. The bias due to misclassification may be reduced.

Key Words: Misclassification, raking, Veterans health, Operation Enduring Freedom, Operation Iraqi Freedom

1. Introduction

The National Health Study for a New Generation of U.S. Veterans (NewGen) was a survey of 20,563 respondents from a sample of 30,000 deployed and 30,000 non deployed veterans in support of Operation Enduring Freedom (OEF) or Operation Iraqi Freedom (OIF). The NewGen survey was designed to provide insight into the overall health of recent veterans through understanding their environmental exposures while deployed, and the short and long term health effects of deployment; in addition, results of this study will be used to inform and improve VA's understanding of the health care needs of OEF/OIF veterans. The analytical objectives of interest were to investigate whether deployment to OEF/OIF affected veterans' health status and to compare health outcomes between the deployed and non-deployed veterans. An essential component of such analysis is the construction of weights that account for the sampling design (stratified random sampling) and survey nonresponse.

The population for the NewGen survey consisted of living veterans who served in the military between October 1, 2001 and June 30, 2008. Coast Guard veterans were excluded due to their small numbers and veterans born in 1985 or after were also excluded. The NewGen sampling frame was designed from two rosters of service members. The deployed frame included veterans from the Department of Defense (DoD) Defense Manpower Data Center (DMDC) who were deployed in support of OEF/OIF and subsequently separated from active duty or deactivated from their National Guard or Reserve service. This file contained 925,650 unique OEF/OIF veterans who were separated or deactivated as of June 30, 2008. The sampling frame for non-deployed veterans was designed using the VA/DoD Identification Repository (VADIR), containing 1,133,008 veterans, who were not in the DMDC roster. After application of inclusion/exclusion criteria, the NewGen sampling frame contained 893,939 deployed and 957,268 non-deployed veterans.

In the sampling design, the population was stratified according to: deployment status; gender; service (Army, Air Force, Navy, or Marines); and component (Active Duty, Reserve, or National Guard) (Table 1). Within each stratum, a sample of veterans was selected through simple random sampling, by which sample size was allocated so that each subgroup was adequately represented in both the deployed and non-deployed veterans. Female veterans were oversampled, so that they represented 20 percent of the sample.

Like other large, complex surveys, the NewGen survey had notable nonresponse—34% of the sample responded [2]. This response rate prompted a nonresponse bias analysis that assumed a missing-at-random mechanism with the four sampling variables and additional variables for education and age; these were shown to correlate with response probability. Statistical adjustment through a weighting technique was used to account for nonresponse, so that the respondent sample represents the target population with respect to these covariates. Our approach included a weighting cell adjustment method [6] that adjusted respondents' weights within cells constructed based on sampling variables plus education and age. In addition, to enhance the precision of the survey estimates it is also common that after nonresponse adjustments the weights of the respondents are post-stratified to some known population distributions/counts. This is carried out to ensure that total count estimates calculated using the analysis weights agree with the known population totals.

Deployment status is one of the key variables for analysis. There are two possible sources for this variable: deployment status in the sampling frame (administrative record) and that from the survey (self-report). In the NewGen questionnaire, the respondents were asked, "Have you been deployed to OEF and/or OIF?" We define self-reported deployment as the answer (Yes/No) to this question and, if Yes, a self-reported period of last deployment after October 1, 2001. It became apparent during preliminary investigation that the deployment status recorded in the NewGen frame and the self-reported status did not agree in many instances. Of 11,337 respondents classified as deployed Veterans in the sampling frame, 490 (4.3%) reported themselves as non-deployed. On the other hand, of 9,226 respondents classified as non-deployed to OEF and/or OIF, 2,315 (25.0%) reported that they had been deployed. The latter instance indicates that the magnitude of misclassification of this type is not trivial and has implications for minimizing statistical bias.

In survey practice, it is common to have discrepancies between values in the sampling frame and the survey. For analyses based on survey data, the surveyed variable usually is used to determine the domain of analysis, since this variable may have less reporting error, especially for demographic variables such as gender, marital status, and education. In the NewGen study, misclassification rates between sampling variables vs. those corresponding self-reported variables for gender, branch of service, and component type are small. However, the misclassification rate for deployment status raised concern. For example, for post-stratification, when the weights of survey respondents are post-stratified to some known population counts, and this population information, contain misclassification; survey estimation in these two groups may be biased because the survey weights are computed based on a sampling frame that uses the misclassified design variable of deployment status. The population totals that these weights represent are affected by the misclassification of deployment status. The analytic consequence is that a survey estimate will possibly be subject to bias.

This type of error will affect estimates of population proportions in that the survey estimates may be biased, with the bias being a function of the magnitude of the misclassification rate and the magnitude of the population proportion itself [5]. Misclassification affects the variance of the survey estimate through inflation due to reduction in the sample size for the category with classification error and differential sampling weights within a stratum caused by the change in stratum membership from the original sampling design [4]. In this paper we demonstrate the use of Kuha and Skinner [5] approach to correct the population totals used as the benchmark to rake the weights.

We discuss a general approach to address misclassification; the impact of misclassification to the NewGen survey; the statistical adjustments needed for misclassification, using a weighting technique that post-stratifies the survey weights to the population totals obtained from updated DMDC and VADIR databases; results for our statistical adjustments in the NewGen survey, and further implications for our work in the context of studying Veteran populations and the effect of deployment exposure on their health conditions.

2. Methods

An important feature of the NewGen survey is that the deployment status of a veteran in the sample may have changed from non-deployed to deployed after sampling in 2008. Sampling was based on administrative records dated June 2008, and survey fielding occurred from August 2009 through August 2010, although responses were accepted through January 2011.

There are numerous reasons why the deployment status in the sampling frame and the self-reported status do not agree. For example, a veteran identified as non-deployed in the survey frame may have in fact been deployed to OEF/ OIF between the time of sampling and survey fielding. The change of deployment status between the time of sampling and the time of survey fielding appears to be a non-ignorable source of misclassification in the survey.

The NewGen survey focused on veterans supporting OEF/OIF who were deployed after October 1, 2001, but otherwise did not consider a time reference for the deployment status; however, the analysis implicitly considers one. Specifically, while the sampling frame identified these populations at a given point in time (June 2008), the health outcomes of Veterans are recorded well beyond that date. For example, if the sampling variable for deployment status is used as the domain of analysis, sampled Veterans whose status changed from non-deployed to deployed cannot remain in the non-deployed group because their health outcomes may have been affected by OEF/OIF combat exposure. As such, the domain of analysis for deployment status should use the self-reported deployment status from the survey instead of that recorded in the sampling frame.

Here we consider three causes of misclassification that led to discrepancies between deployment in the sampling frame and deployment that was self-reported. These causes are as follows:

1. A service member was identified as deployed in the sampling frame, along with his or her unit, but otherwise self-reported in the survey as non-deployed. In the DMDC file, deployment status is recorded at the level of the deployment unit, so if an individual service member had not deployed with his or her unit, the DMDC file may not correctly reflect this status. This is an administrative error due to undocumented removal from the deployment unit.

2. A service member was identified as non-deployed in the sampling frame but self-reported in the survey as having been deployed prior to sampling. This is an administrative error due to incorrect deployment status in the VADIR file. In this case, the veteran was deployed prior to sampling and reported this in the survey; however, the veteran was incorrectly documented as non-deployed in the VADIR file and also was not included in the DMDC file.

3. A service member changed in deployment status over time. The sampling frame was created as of June 30, 2008, and survey fielding began in August 2009. A service member who had originally been identified as non-deployed in the frame was eventually deployed to a combat theater in support of OEF or OIF between the time of sampling and the survey response.

Given the period of deployment information available from the survey response, as well as from the administrative data, we can identify the individual classification errors cited above (Table 2).

These classification errors affect the basic sampling weights calculated based on the June 2008 sampling fame using the misclassified deployment variable. Given the information in Table 2, the misclassification sampling frame can be estimated. Our approach is to use a misclassification matrix representing the misclassification error to update frame totals to account for misclassification and then implement raking with these adjusted frame totals.

To address the deployment status change (classification error 3), it is possible to use updated administrative data to determine the deployment status of the veterans at points in time during survey fielding. A DMDC file (January 2011) provides updated deployment status, for records linked to the original sample; the information from the original sampling frame otherwise remains the same. We note in Table 3 that the misclassification due to deployment status change (classification error 3) between June 2008 and January 2011 has been reduced. Our investigation suggests that the misclassification rates already had stabilized towards the end of data collection; otherwise, alternate roster dates could have been considered. The use of an updated DMDC roster to identify misclassification, however, gives rise to the possibility of an additional misclassification type, which we briefly describe as follows:

4. A NewGen respondent returned the completed survey before January 2011 and self-reported as non-deployed. Subsequently, the veteran was deployed to OEF/OIF, and the updated DMDC file reflects this deployment. (This misclassification differs from misclassification type 1; veterans under misclassification type 1 may have had deployment dates posted prior to their survey response, while misclassification type 4 veterans had deployment dates *after* their survey responses.)

Figure 1 illustrates the timeline of events that occurred from the time of sampling through the end of the NewGen survey.

Table 3 shows the frequencies and rates of misclassification in relation to the updated file for the four situations we have described. As a consequence of using June 2008 as the sampling frame, classification errors 2 and 3 are reduced. However, 69 type 4 misclassification cases are created. We compared misclassification matrices derived from Tables 2 and 3, and obtained the adjusted control totals from these matrices to adjust the survey weights by raking. The misclassification in these files was addressed using the matrix method [5].

Post-stratification techniques are generally used to address misalignment between the design and/or key survey variables in the survey data compared to those in the population due to survey nonresponse and "frame coverage." When known population counts or proportions are available, either from external sources or an updated sampling frame, the survey weights can be post-stratified to these counts so that the survey estimate will have greater precision [6]. When only marginal known population totals of these variables are available, raking can be used as an alternative to post-stratification. Raking is an iterative process that post-stratifies one variable at a time, with the goal that the weighted counts for all variables will eventually be the same as (or closely approximate) the known population totals [1,6]. The updated DMDC file provided known population totals for benchmarking in raking. Using this file, misclassification due to temporal change in deployment status (misclassification error type 3) can be resolved. However, the updated file still contained possible misclassification due to true administrative errors. To deal with this, we first implemented the total count adjustments [5] for misclassification in categorical data analysis. The deployment misclassification-adjusted frame counts based on the updated file were then used for control totals in raking.

We used a method utilizing a matrix representing misclassification rates to account for misclassification error [5]. For a categorical variable with m categories, denote the true classified variable by A and the misclassified variable by A^*. The proportion of units with a category k misclassified into category j is defined as

$$\theta_{jk} = Prob(A^* = j|A = k), \quad j,k = 1,\cdots,m.$$

The $m \times m$ misclassification matrix is defined by

$$\Theta = \begin{pmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1m} \\ \theta_{21} & \theta_{22} & \cdots & \theta_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{m1} & \theta_{m2} & \cdots & \theta_{mm} \end{pmatrix}$$

where the columns represent A and the rows represent A*, and where each column sums to one. When there is no misclassification in the population, Θ is an identity matrix.

To construct this matrix for the NewGen survey, we required the true and misclassified deployment statuses for each Veteran. However, we did not necessarily have the true value of deployment status for each Veteran; rather, we had the true and misclassified values only for a subset of the population responding to the survey. In this situation, we estimated the misclassification matrix using cases for which both variables are available. The counts used to calculate $\hat{\theta}_{jk}$ are total estimates weighted by the nonresponse adjusted weights, so that $\hat{\theta}_{jk}$ has the usual properties of the survey estimator as discussed in [6].

Let $P_A = \left(P_A(1), \dots, P_A(m)\right)^T$ denotes the true population proportions of variable of interest A with m categories, where A may be defined as a cross classification of several variables. In practice, the estimator (weighted) sample mean/proportion of P_A—denote by $\hat{P}_{A^*}$, based on the current nonresponse-adjusted weights with misclassified sample is often used. Under correct classification and the sample design, the individual element of $\hat{P}_A$ may not be design unbiased, but efficient estimator. With misclassification, $\hat{P}_{A^*}$ estimator may not be even consistent because the sample was designed based on a misclassified variable. Instead, using the relation

$$E\left[\hat{P}_{A^*}\right] = \Theta P_A$$

the misclassification-adjusted estimate of P_A can be calculated as

$$\hat{P}_A^m = \hat{\Theta}^{-1}\hat{P}_{A^*} \qquad (1)$$

where $\hat{\boldsymbol{\Theta}}$ is the estimate of Θ. Note that matrix $\hat{\boldsymbol{\Theta}}$ needs to be nonsingular so that its inverse exists. In addition, each element of the multiplication on the right-hand side of equation (1) must be within the range of zero to one.

This misclassification-adjusted proportion estimates are then multiplies by the population size $\boldsymbol{N}$ to get the misclassification-adjusted totals $\hat{\boldsymbol{N}}_{\boldsymbol{A}}^{\boldsymbol{m}} = \hat{\boldsymbol{P}}_{\boldsymbol{A}}^{\boldsymbol{m}}\boldsymbol{N}$. Then, $\hat{\boldsymbol{N}}_{\boldsymbol{A}}^{\boldsymbol{m}}$ are used in raking.

In the NewGen survey, this matrix was estimated using self-reported deployment status and the deployment status in the sampling frame; the misclassification proportions were calculated as weighted proportions, since these proportions were dependent on the differential response rates between deployed and non-deployed groups. The deployment status misclassification matrix, estimated in the sample and denoted by

$$\widehat{\boldsymbol{\Theta}} = \begin{pmatrix} \widehat{\boldsymbol{\theta}}_{\mathbf{11}} & \widehat{\boldsymbol{\theta}}_{\mathbf{12}} \\ \widehat{\boldsymbol{\theta}}_{\mathbf{21}} & \widehat{\boldsymbol{\theta}}_{\mathbf{22}} \end{pmatrix},$$

is given in Table 4 for the June 2008 sampling frame and the January 2011 updated sampling frame. It is easy to show that in this binary variable, the matrix will not be singular, unless $\widehat{\boldsymbol{\theta}}_{\mathbf{11}} + \widehat{\boldsymbol{\theta}}_{\mathbf{22}} = \mathbf{1}$.

The off-diagonal elements of $\widehat{\Theta}$ are the estimated misclassification rates. When there is no misclassification in the sample, $\widehat{\Theta}$ is the identify matrix.

Since the updated deployment status provides less classification error, we proceeded to the control total adjustment for raking using these data. The adjustment changed the total counts from 905,431 (49%) non-deployed Veterans and 945,776 (51%) deployed Veterans to 818,660 (44%) non-deployed Veterans and 1,032,547 (56%) deployed Veterans. These adjusted control totals were then used in the weight raking.

The weights were raked to the frame counts, where raking cells were constructed as combinations of the following six variables: self-reported deployment status, gender, service branch, component, highest education, and birth year cohort. In our adjustments of the weights, we used raking rather than post-stratification technique. We had observed that post-stratification cells based on the combinations of these six key variables resulted in sparse cells, which would lead to unnecessary fluctuation of post-stratification ratios and unstable variances due to extremely large weights.

3. Results

We looked at the estimates of proportions for six variables computed based on survey respondents, using the nonresponse-adjusted weights and final raked weights, and compared these proportions to the proportions based on a sampling frame with the updated deployment status (Table 5). As the response rates were different across some of these six variables, nonresponse-adjusted weights account for these differential response rates. Raking to the adjusted control totals further attenuated the misclassification in deployment status.

The main source of classification errors in the deployment status sampling variable appears to be exclusion of deployed veterans in the roster used to develop the sampling frame. Our investigation of both the June 2008 and updated January 2011 rosters indicated that approximately 8% of veterans who self-reported as deployed to OEF/OIF were not listed in the DMDC roster. In addition, some classification errors arose because survey participants possibly experienced a change in their deployment status between the time of sampling and the time of survey completion. In this exposition, we have addressed those features, not unusual for the Veteran population, of the study that concerned the survey reference period and temporal changes in deployment status. A consideration for future iterations of the NewGen survey would be to impose a reference period for deployment status that aligns with the deployment period in the sampling frame. In this first iteration of the survey, this type of misclassification was inevitable, given the ongoing conflicts and the demand for personnel resources in OEF and OIF.

We note that misclassification errors in the NewGen survey could not be avoided completely. We have provided statistical approaches that generally reduce misclassification to the furthest extent possible using updated deployment roster files. Without accounting for misclassification, survey estimates involving totals computed using survey weights are potentially biased, especially for analysis involving misclassified deployment status. We performed raking when the benchmarked population counts for deployment status were estimated so as to correct misclassification. Using estimates rather than "true" counts, however, could introduce additional variation. Nevertheless, the bias due to misclassification may be reduced.

The final raked weights accounting for deployment status misclassification may provide adequate point estimates in NewGen analyses. The analysis goal in the NewGen study will involve variance estimation, for which hypothesis testing will be carried out in comparing deployed and non-deployed veterans. Design-based estimation for variance estimates under the usual Taylor series method using these weights, however, may not fully account for the complicated statistical adjustments performed during weighting; these included nonresponse adjustments, misclassification-adjusted control totals, and raking [3,8] As an alternative, variance estimation under replication methods may be used [7].

A misclassification matrix used to adjust raking control totals can be sensitive to the response rate within the groups of misclassified variables, specifically, if the response rates should be different between deployed and non-deployed groups. As noted by Kuha and Skinner [5], the bias of a misclassified estimate will not go away even when the proportions of misclassifications are equal between those of status change from deployed to non-deployed (false positives) and those of status change from non-deployed to deployed (false negatives). We have included survey weights in estimating such proportions to account for differential response rates between deployed and non-deployed groups. Given a misclassification matrix computed based on survey response outcome, the adjusted control totals can be significantly different than the original frame counts. Nevertheless, further evaluation of these adjusted estimates may be needed, using better administrative records.

3. Discussion

Misclassification is a common type of error found as part of non-sampling errors in a sample survey. It may exist even when the variable has been clearly defined conceptually and the survey has implemented a clear survey reference period. Imperfections in the DMDC and VADIR administrative data may have caused true misclassification error in the sense that incorrect information was obtained from the roster files. As we note in Table 3, updated information can reduce the error to some extent, but not entirely; however, in this type of investigation, it is important to understand the cause of such misclassification, particularly regarding the implications for analysis of an environmental exposure and its health outcomes. Use of updated information has informed our approach for the possible types of misclassification discussed previously. We note that misclassification type 3 errors occurred mainly because the NewGen study did not explicitly impose a survey reference period for deployment status. Misclassification type 3 errors could have been avoided if, for example, the reference period for deployment status had been defined as those deployments occurring prior to June 2008. Defining the reference period in this way would have rendered "ineligible" those veterans whose deployment status had changed since the time of sampling (from non-deployed to deployed); thus, they would have been excluded from analysis because they were not part of the defined target population. As it currently stands, the NewGen survey included these veterans as part of the target population and had collected data from their cases. Excluding these 612 survey responses would result in a waste of valuable resources already spent in data collection. Analysis of the eligible sample (for which eligibility is defined post hoc by excluding cases with a changed deployment status) may produce biased estimates of survey outcomes, especially if the veterans deployed prior to June 30, 2008 differed on important characteristics from those with a changed deployment status (deployed after July 1, 2008). On the other hand, if the study were to retain the latter in the non-deployed group instead (that is, the domain of analysis was defined using the deployment status at the time of sampling), it likely would induce bias in the analysis of their health outcomes because they had in fact experienced deployment exposure.

Aligning the sampling frame with the updated records generally reduced misclassification rates, especially that of misclassification error type 3; in fact, we note in Table 3 that the number of misclassified cases from non-deployed to deployed decreased from 2,315 to 1,774, a reduction of 541 misclassified cases between frames based on the June 2008 and January 2011 DMDC rosters. However, it is important to note that the updated DMDC rosters may still contain misclassification. For example, alignment of the sampling frame might not account for veterans who reported being non-deployed in their returned surveys (an early respondent) but in fact subsequently had been deployed; their status then would be indicated as deployed in the updated roster. Balancing this concern, we note, as evidenced in Tables 2 and 3, that a majority of cases misclassified from non-deployed to deployed would be reduced considerably at the expense of some induced misclassification error type 4 (69 cases). With only a little effort in using the updated DMDC file, we can mitigate concerns about differences in administrative and self-reported deployment status, as well as concerns about their causes, and can use standard approaches for adjusting the rest.

In future applications, we will show the impact of misclassification adjustments in analyses of NewGen survey outcomes. The analyses will include computed standard errors for the survey estimates of deployment and non-deployment rates used in the misclassification matrix, as well as estimation of key survey outcomes and their variances. Comparisons of alternative approaches to misclassification will greatly inform the appropriate use of them in this and broader contexts.

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Table 1 Frame and Sample Counts, by Sampling Cell

		Frame Count				Sample Count			
		Deployed		Non-deployed		Deployed		Non-deployed	
Component	Branch	Female	Male	Female	Male	Female	Male	Female	Male
Active Duty	Army	22,823	161,275	46,503	148,889	1,003	3,762	1,003	3,762
	Air Force	14,129	67,502	28,577	94,527	621	1,575	621	1,575
	Marine	2,949	81,026	6,180	59,682	130	1,890	130	1,890
	Navy	14,707	101,706	24,078	116,385	646	2,373	646	2,373
Guard	Army	14,775	169,593	21,126	106,033	1,111	4,925	1,111	4,925
	Air Force	6,507	50,786	6,378	21,096	489	1,475	489	1,475
Reserve	Army	16,771	85,269	33,551	91,116	1,345	4,231	1,345	4,231
	Air Force	4,188	26,767	13,604	30,977	336	1,328	336	1,328
	Marine	656	26,694	4,707	51,376	53	1,324	53	1,324
	Navy	3,314	22,502	12,788	39,695	266	1,117	266	1,117

Table 2 Count and Percentage, Weighted Count and Weighted Percentage of Deployment Status Reported in the Sampling Frame and Survey

Deployment status in the sampling frame (June 2008)	Self-reported deployment status			
	Non-deployed	Deployed		Total
Non-deployed		Admin error (2)	Changed status (3)	
	6,911	1,703	612	9,226
	33.6%	8.3%	3.0%	44.9%
	(235,357)[a]	(48,055)	(14,327)	(297,738)
	(37.4%)	(7.6%)	(2.3%)	(47.4%)
Deployed	Admin error (1)			
	490	10,847		11,337
	2.4%	52.8%		55.1%
	(13,812)	(316,934)		(330,746)
	(2.2%)	(50.4%)		(52.6%)
Total	7,401	13,162		20,563
	36.0%	64.0%		100%
	(249,169)	(379,315)		(628,484)
	(39.6%)	(60.4%)		(100%)

a. Weighted count and weighted percentage of deployment status are in parentheses.

Table 3 Count and Percentage, Weighted Count and Weighted Percentage of Classification Errors in the Updated Sampling Frames

Deployment status in the updated DMDC roster (January 2011)	Self-reported deployment status				
	Non-deployed		Deployed		Total
Non-deployed			Admin error (2)	Changed status (3)	
	6,854		1,601	173	8,628
	33.3%		7.8%	0.8%	42.0%
	(234,182)[a]		(45,495)	(4,470)	(284,147)
	(37.3%)		(7.2%)	(0.7%)	(45.2%)
Deployed	Admin error (1)	Post-survey deployment (4)			
	478	69	11,388		11,935
	2.3%	0.3%	55.4%		58.0%
	(13,470)	(1,517)	(329,351)		(344,337)
	(2.1%)	(0.2%)	(52.4%)		(54.8%)
Total	7,401		13,162		20,563
	36.0%		64.0%		100%
	(249,169)		(379,315)		(628,484)
	(39.6%)		(60.4%)		(100%)

a. Weighted count and weighted percentage of classification errors are in parentheses.

Table 4 Estimated Misclassification Matrix for the June 2008 and January 2011 Frames

2008			2011		
	True status			True status	
Misclassified status	Non-deployed	Deployed	Misclassified status	Non-deployed	Deployed
Non-deployed	0.934 (0.945)[a]	0.176 (0.164)	Non-deployed	0.926 (0.940)	0.135 (0.132)
Deployed	0.066 (0.055)	0.824 (0.836)	Deployed	0.074 (0.060)	0.865 (0.868)
Total	1	1	Total	1	1

a. The numbers in parentheses are weighted proportions.

Table 5 Percentages in the Updated Frame and Those Based on Survey Estimates, by Six Key Variables

Variable	Sampling frame as of June 2008	Updated sampling frame (January 2011 deployment status)	Survey estimates using nonresponse-adjusted weights	Survey estimates using final raked weights
Deployment Status				
Non-deployed	51.7	48.9	43.0	44.2
Deployed	48.3	51.1	57.0	55.8
Gender				
Women	16.1	16.1	16.1	16.1
Men	83.9	83.9	83.9	83.9
Component				
Active Duty	53.5	53.5	53.5	53.5
National Guard	21.4	21.4	21.4	21.4
Reserve	25.1	25.1	25.1	25.1
Service Branch				
Army	49.6	49.6	49.5	49.6
Air Force	19.7	19.7	19.9	19.7
Marine	12.6	12.6	12.6	12.6
Navy	18.1	18.1	18.0	18.1
Birth Cohort				
<1960	9.0	9.0	8.7	9.0
1960–69	20.7	20.7	20.6	20.7
1970–79	30.5	30.5	30.8	30.5
1980-1985	39.8	39.8	39.9	39.8
Highest Education				
≤ HS Diploma or unknown	72.5	72.5	72.2	72.5
Some College	12.5	12.5	12.5	12.5
Baccalaureate Degree	10.4	10.4	10.7	10.4
Post-Baccalaureate Degree	4.6	4.6	4.7	4.6

Figure 1 Timeline of the NewGen Survey and Points in Time at Which Misclassification Types Can Occur