Standardizing and Democratizing Survey Weights:

The ANES Weighting System and anesrake

Josh Pasek

University of Michigan

Matthew DeBell

Jon A. Krosnick

Stanford University

July 26, 2014

The authors are indebted to the members of the ANES advisory committee who met to recommend guidelines for the weighting strategy proposed here. The ANES committee members were Doug Rivers (chair), Martin Frankel, Colm O'Muircheartaigh, Charles Franklin, and Andrew Gelman. Recommendations proposed in this paper were all endorsed by committee members, though not every committee member agrees with every recommendation in the memo. The authors also thank Andrew Hansen for assisting with data analysis. Address correspondence to Josh Pasek, 105 S. State Street, 5413 North Quad, Ann Arbor, MI, USA 48103. Phone: +1-734-764-6717. Email: jpasek@umich.edu.

Abstract

The current manuscript builds on the report of a panel of weighting experts assembled by the American National Election Studies. In it, we outline the process of raking to produce survey weights, propose default raking choices in order to standardize the process of generating raked survey weights, and present *anesrake* package for *R,* a piece of software designed to broaden the capacity of individual researchers wishing to create weights attuned to their analyses. The paper's contribution is a freely accessible, transparent, and replicable method for calculating survey weights.

"Weighting may be more an art than a science, but it is an art with many successful practitioners." (Gelman, 2007a, p. 89)

To many survey researchers, weighting is often a methodological a black box. The statistical principles that justify using weights are firmly established (Horvitz & Thompson, 1952; Kish, 1965), yet weights emerge from a process that is opaque, or at least cloudy, to most producers and consumers of survey data (Breidt & Opsomer, 2007). Moreover, the firmly established principles of weighting are not accompanied by well-established practice for the computation of weights, and survey researchers have little guidance in the mechanics of doing so. Hence, despite the fact that most scholars have been taught to include weighted data in their analyses, few know where those weights come from, what kinds of decisions are involved, or what the implications of those decisions might be, and weighting practices are quite varied. This has led to the widespread sense that weighting is more art than science, as exemplified by Gelman's statement.

To make weighting more accessible, transparent, consistent, and scientific this paper provides a step-by-step description of a new set of procedures for weighting survey data that improve its accuracy while minimizing variance. The paper also describes new free software we have developed to implement these procedures, and compares the accuracy and precision of survey estimates made using these procedures to estimates made using more conventional weights.

Background

Until very recently the literature whose audience is aspiring and practicing survey research professionals has included almost no details telling researchers how they might go about constructing weights for sample surveys of individuals. The authoritative Groves et al. (2009) *Survey Methodology* textbook contains just two paragraphs on poststratification weighting, and it is not alone in neglecting the subject. Other works billed as general, "comprehensive," or "step-by-step" guides to survey research mention weights only in passing (e.g. J. Blair, Czaja, & Blair, 2013) or not at all (e.g. Fink, 2009; Rea & Parker, 1992). The more specialized and technical literature that does address weighting in depth tends to focus on questions that are important for the advancement of statistical theory but whose purpose is not to help standardize everyday practice or to provide a start-to-finish guide to optimal weight construction (e.g. Bethlehem, 2001; Gelman & Carlin, 2002; Lee & Valliant, 2008). One exception is Dorofeev and Grant (2006), which notes that the topic "is generally ignored in texts on statistics and on survey research" (45) and provides a useful discussion. More recently, Valliant, Dever, and Kreuter (2013) have stepped into the breach with *Practical Tools for Designing and Weighting Sample Surveys*.

For want of specific guidance in the literature, it is not surprise that weighting remains in many respects more an art than science. Without step-by-step procedures having been articulated in accessible literature, practitioners were left to their own judgment in applying general statistical principles to specific situations. Predictably, this has resulted in widely varying practices (Voss, Gelman, & King, 1995).

At the American National Election Studies (ANES), which is the longest-running major survey research project in the social sciences, the lack of standardization is reflected the study's time series of data that spans more than 60 years. ANES has conducted nationally representative face-to-face surveys in most even-numbered years since 1948. For the earlier studies there are no weights at all. For some studies it is possible to account for the probability of respondent selection by accounting for household size, but no other weighting factors are available. For other studies, poststratified weights are available, but these weights were computed using relatively rudimentary methods that may leave important biases uncorrected (see e.g. Campbell, 2010).

Scholarship would benefit in several ways from having a standardized process with accessible tools for developing survey weights. Costs would be lower. Reasonably good weights could more easily be created within a shorter period of time. Perhaps most importantly, methodological transparency would be fostered, making results more easily replicable, making studies more comparable to one another, and providing a common reference point for ongoing methodological criticism and improvement. With these aims in mind, in 2008 the ANES began a process of developing best practices for weighting and convened a committee of experts in survey methodology and statistics to help guide the study. This paper builds upon that work as it was reported by DeBell & Krosnick (2009) and extended by Pasek, DeBell, and Krosnick (2010).

Plan of the Paper

This paper outlines a standardized approach for developing weights using raking (a.k.a. rim weighting or iterative poststratification). We do not recapitulate the statistical foundations of weighting or survey the literature on these methods, as this ground has been covered elsewhere (e.g. Lohr, 2009).

The remainder of the paper has five parts. We begin by describing the raking procedure and identifying a series of decisions that researchers must make when producing weights. For each of these decisions, we discuss implications of the choices for the eventual weights and propose a baseline standard choice in the absence of compelling alternatives. Second, in a step-by-step summary of the raking process, we list the steps to follow to make and implement the necessary choices. Third, we present the *anesrake* package in *R*, which was designed to provide a simple, accessible interface for implementing these choices. Next, we present an example of the application of the procedure to a dataset. Finally, we discuss the assumptions built into all raking procedures to highlight the advantages and limitations of the proposed approach.

The Raking Procedure

Raking is a relatively simple procedure designed to correct for known survey errors. The strategy produces a series of survey weights that ensure that the weighted survey results match target distributions for predefined, typically demographic, categories. First proposed by Deming (1940), raking accomplishes this by minimizing the Kullback-Leibler (KL) divergence for each variable in an iterative fashion and repeating this process until no additional convergence is achieved (Ireland & Kullback, 1968). Research has shown that this iterative poststratification process converges on the target marginal distributions in a log-linear fashion (Darroch & Ratcliff, 1972; Fienberg, 1970).

Many, if not most, probability sample surveys are subjected to a raking procedure before dissemination to ensure that survey results are demographically similar to the public (cf. Voss et al., 1995). Researchers have long noted that raw survey data tends to underrepresent certain demographic groups (e.g. 18- to 24-year-olds, Hispanics, and men in U.S. telephone surveys) when compared to the best population estimates (cf. Michalos & Orlando, 2006). By increasing the weight of data from these populations while decreasing the weight of data from overrepresented groups – a process that raking accomplishes – researchers can produce summary statistics for a sample that are more closely aligned with the target population.

To conduct raking, researchers first need to identify categorical variables that will be used in the weighting process. In a series of steps, the survey proportions for each variable of interest are compared to known population proportions for the same variables and adjusted to match those figures. Survey proportions can be adjusted by multiplying the weights of a dataset by a ratio of the population proportion divided by the survey proportion. As an example, one can imagine a sample of the American public that happened to be 45% male and 55% female. The actual US population (according to the concurrent weighted Current Population Survey) was instead 48% male and 52% female. To adjust the data, each man in the sample would then have his weight multiplied by 48/45, and each woman in the sample would have her weight multiplied by 52/55. The sums of the weights for men and women would then reflect the proportions in the population.

This procedure is then repeated with each variable that the researcher wishes to account for. If the second variable used for weighting was race, the raking procedure would use the weights created from gender to determine the weighted percentage of individuals of each race. To extend our example, we might imagine that 80% of the newly weighted sample was non-Hispanic White, 7% of our sample was non-Hispanic Black, 7% of our sample was Hispanic, and 6% of our sample was some other non-Hispanic group; actual population distributions were 69% White, 11% Black, 13% Hispanic, and 7% Other. The new weights for each individual would then be the old weights multiplied by the ratio between the sample proportions and the population proportions. Hence, the new weights for a White, non-Hispanic individual would be equivalent to *old weight* * 69/80.

Raking continues until the sample has been adjusted for all of the variables – a single iteration. Because adjustment of later categories can disrupt matching proportions for earlier categories, the raking process is repeated until one of two things happens: (1) The procedure fully converges such that the weighted sample percentages for all categories perfectly match the population percentages or (2) the procedure is not able to converge any further even though the weighted sample percentages do not perfectly match, which could happen if the data and the targets are incompatible.

Choices in Raking

Although the basic premises of raking are simple, there are a number of choices that must be made before raking can proceed. These choice points are to (1) define starting weights for the raking procedure, (2) identify relevant survey respondents, (3) conduct a benchmark comparison, (4) choose and configure variables for raking, (5) set parameters for iterative weighting, (6) check and adjust the procedure depending on results, and (7) scale the final weights. We discuss each of these choice points in turn and specify recommendations based closely on the suggestions of the ANES panel (DeBell & Krosnick, 2009) and the literature.

Starting weights. Before raking, survey design procedures typically result in unequal probabilities of selection across individuals. Correctives can and should be employed to adjust for the variations in likelihood of selection that occur as a function of multi-stage designs, clustering of respondents, and nonresponse rates of clearly defined strata. These corrections will produce base weights that should be used to initiate a raking procedure.

As much as possible, base weights should be calculated to yield results inversely proportional to each individual's probability of selection. For example, households (or individuals) that can be accessed through multiple routes should be downweighted in proportion to the number of ways that that household can be accessed. Conversely, when the sampling units are larger than the units of observation (e.g. when households are sampled, but individuals are recruited), weights should be increased in proportion to the number of eligible individuals that could be sampled (e.g. adults in the household). Unequal rates of nonresponse can sometimes be inverted in this same manner when response rates are available for subpopulations smaller than the entire survey (e.g. by region).

Identify relevant respondents. Although weights often appear as an additional variable with values for each individual, they are not individual attributes. Instead, weights index how each particular individual should be understood in the context of results from the entire data collection procedure. In this vein, removing some individuals from the dataset or conducting the analysis on a subset of the data will change how individuals relate to the overall data collected and thus should alter the weights of all individuals examined. The researchers' comparison of interest should therefore guide the decision of which individuals should be included in the weighting procedure.

Weights should therefore be generated using only the subset of individuals whose data will be examined. This means that weights for an analysis of individuals registered to vote should be generated for individuals in the sample who are registered to vote and should be weighted using benchmarks for individuals registered to vote in the population. Similarly, for an analysis of individuals who completed two-waves of a multi-wave panel, weights should be developed only for those individuals who were present in both waves. Analyses of data with planned missingness or where data for the outcome variable is missing for many cases will also produce more accurate results if weights are limited to the cases being analyzed.

Conduct a benchmark comparison. The foundation of raking procedures is accurate knowledge of population characteristics. A census, a highly reliable sample survey such as the Current Population Survey or American Community Survey, or other reliable data source may be used to identify population characteristics for comparison to the sample. This comparison should be performed for as many variables as practical, provided that the survey and the benchmark use comparable measures.

Select and prepare variables for poststratification. Like all weighting procedures, raking is sensitive to the number and nature of the variables used for correction. As more variables are employed, the variance of a set of weights will tend to increase. Similarly, as raking variables become more discrepant from known population parameters, adjustments to eliminate biases will tend to increase variance. At some point, attempts to eliminate bias by correcting for additional variables will result in enough added variance that the accuracy of estimates will plateau and eventually diminish (due to the added variance). In this sense, variable selection for raking is fundamentally a balancing act.

Four additional challenges can further complicate the process of selecting variables for raking. One is the compatibility of survey and benchmark statistics. If some variable is inconsistent within individuals across time, weighting this variable to match an outdated benchmark may result in incorrect inferences. Similarly, if measures in the survey do not perfectly match those in the benchmark data, weighting may lead to mischaracterizations of the population. The second challenge is the potential for missing data in either the current survey or the benchmark. Missing data for either can lead to imperfect matches between data streams and can result in mischaracterizations. Third, categories for variables need to have a decent number of respondents to produce stable results. Responses selected by fewer than 5% of respondents should be collapsed with conceptually similar categories for the same variables.

The fourth challenge for the selection of variables for raking concerns comparability across studies. To the extent that different studies have the same design and patterns of nonresponse, studies should have similar weights so that weighting differences do not affect comparisons. However, sample designs and nonresponse patterns may differ between studies and over time, warranting the selection of different poststratification factors on different studies.

Based on these concerns, we recommend that low-nonresponse demographic variables form the basis for any raking procedure. The ANES report specifically names age, sex, race/ethnicity, educational attainment, Census region, marital status, home tenure, and household size as strong candidates (DeBell & Krosnick, 2009). These variables have been shown to produce reliable test-retest estimates (Smith & Stephenson, 1979) and complete benchmark data is routinely available. Where applicable, behavioral reports – such as presidential vote choice and voter turnout – may be useful if variables are theoretically related to the subjects of inquiry. It is important to ensure that benchmarks are comparable for these measures, however.

Because the incorporation of many variables increases the variance of the resulting weights, it is valuable to exclude variables for which little error is present. Hence, ANES advisory panel members recommended excluding variables when the discrepancy between survey and benchmark was less than two percentage points and carefully considering variables for which these discrepancies were smaller than five percentage points. This step helps to limit the size of the design effect[1].

Parameters for weighting. Choosing the variables is far from the last step when raking. The eventual weights produced will sometimes depend on the ordering by which variables are introduced into the model, whether researchers wish to avoid large (and also potentially small) weights, and how missing data should be handled. Although the order of insertion for variables is arbitrary, the eventual weights will depend on these decisions, especially if convergence is incomplete. In order to achieve replicable results, it is important that researchers follow a consistent practice for inserting variables. We propose a system of starting with the variables with the largest discrepancies and proceeding toward variables with the smallest discrepancies. Under this system, incomplete convergence will tend to match on the largest number of variables.

The presence of very large weights can lead to analyses that are sensitive to the reports of but a few individuals. One strategy for avoiding this possibility is limiting the influence that individuals can have by setting a maximum potential weight. In the context of raking this is called capping; caps are typically set to limit the maximum influence of an individual. Some firms also set minimum values for weights as this reduces the variance of weights as well, although the theoretical advantage to doing so is less clear as there is no substantive harm from very small

[1] The design effect describes how much the weights (or other aspects of the survey design) increase the variance and the sampling errors of survey estimates, or conversely reduce the survey's precision or the effective sample size. Each survey estimate has its own design effect. If the weights are scaled to a mean of 1 then the average design effect can be computed as the sum of the squared weights divided by the sum of the weights. Design effects for simple random samples are 1. Design effects greater than 1 are typical and reflect an increase in variance due to weighting.

weights and weighted results are likely to be less effective at matching benchmarks. Capping large weights only is therefore recommended and capping those weights at 5 times the mean user's value has been proposed as a good rule of thumb.

One important note about capping is that many firms and much available software only empower users to cap weights after the weighting process has completed. This provides suboptimal results, as there is no potential to correct for the truncations introduced by capping. If weights are instead capped following each iteration, subsequent iterations have the potential to tweak the results such that they are a better fit for the benchmarks while staying under the cap. We therefore recommend that weights be iteratively capped rather than only truncated at the end. Further, we recommend that weights be run both with and without a cap so that the effects of capping can be assessed. If most respondents whose weights are at the capped value share a certain demographic characteristic, then capping is likely to cause biased estimates relating to that characteristic. Raising the cap would be warranted in such cases.

A final decision in running iterative raking is how to handle missing data. Although large amounts of missing data are grounds for omitting variables from the raking procedure, smaller amounts of missing data can be handled in a few ways. Two of the best options are imputing values for missing cases using a procedure such as multiple imputation or ignoring cases with missing values when raking for each variable. Imputation may be somewhat preferable on statistical grounds. However, in the interest of replicability and expedience, ignoring missing values is also a satisfactory approach, particularly when the proportion of missing data is very low. Notably, the raking procedure will produce more accurate estimates if cases with missing values are only ignored when raking to targets for the variable with missing data. When a case is ignored the weights for ignored cases should remain constant.

Assess and adjust. It is not always that case that raking will achieve a perfect match for targeted benchmarks. If raking does not fully converge, the target variables will not be matched. Also, raking on one subset of target variables can lead other variables to deviate from known population values. Hence, it is important to look at the products of a weighting algorithm to assess whether the weights achieve the researcher's goals.

When a sample is not balanced on variables used in raking after the procedure, this usually implies that either the parameters of the weighting or the targeted population values are too strict to allow convergence. Convergence can often be achieved by collapsing categories for some raking targets or by relaxing the caps on weights. These steps should be considered if a sizable imbalance remains after weighting.

In some cases, weighting on a series of variables that diverge from population estimates can lead other variables to stray from their targets. In particular, when using only variables with large discrepancies to produce weights, discrepancies for other variables of interest may be exacerbated. Researchers should be sure to include these variables in the weighting procedure to ensure that weights are proximal to all targets.

Several adjustments are possible when differences between benchmarks and weighted survey results persist after weighting. Options include using a smaller difference threshold for including variables in weighting, using more or smaller categories for the raking variables, raising the weighting cap or omitting capping, or adding or replacing raking variables. Conversely, when weighted results are accurate but the design effect is too high, options include allowing larger differences between the survey and the benchmarks to go uncorrected, using fewer or larger categories for the raking variables, reducing the cap, and excluding raking variables.

Scale the final weights. After weights are computed they may be re-scaled for analytical convenience according to researchers' preferences. Weights may be scaled to a mean of 1 so that the sum of the weights equals the sample size. Alternatively, weights may be scaled to sum to the population size, which is necessary if estimates of subgroup population totals are desired. Weights may also be scaled to sum to the effective sample size, adjusted for the design effect, for purposes of generalized variance estimation methods to approximate sampling errors.

Step-by-step Summary of the Raking Process

In Exhibit 1 we condense the previous discussion of raking into a concise and precise description to steps to follow when raking survey data. The Exhibit adapts text from DeBell & Krosnick (2009).

Exhibit 1. Summary of Raking Process

1. Define starting weights
    a) Assign a base weight equal to the inverse of the probability of selection for each respondent, accounting for all sampling stages.

    b) When response rates are known to vary among sample elements by an observable characteristic, such as by region, adjust the base weight by multiplying by the inverse of each subgroup's response rate.
2. Identify relevant survey respondents
    a) Identify respondents who will be included in analysis, such as all respondents who completed an interview, or those who completed all waves in a panel study, or any subgroup of special interest.
3. Conduct a benchmark comparison.
    a) Using the study questionnaire, identify a set of variables likely to be measured with little error in the survey and with a low item nonresponse rate and compare their distributions with "truth" benchmarks from a reliable source. Perform this comparison for as many variables as practical.
    b) Survey statistics calculated for initial benchmark comparisons should use a base weight that accounts for unequal probabilities of household selection, respondent selection, and nonresponse.
4. Select and prepare variables for poststratification.
    a) If the benchmark comparison reveals notable demographic discrepancies are observed for some variables, poststratification weighting with these demographics should be done. What constitutes a notable demographic discrepancy is a matter of judgment. Often, demographic discrepancies exceeding 5 percentage points are "notable" and discrepancies less than 2 percentage points are not. Discrepancies in the 2 to 5 point range may be notable if the characteristic is of special interest for the study or is strongly associated with key outcome variables.
    b) Select only poststratification factors that are believed to be measured accurately and that have low item nonresponse rates. Variables with item nonresponse rates exceeding 5 percent (as income often does) may not be suitable poststratification factors.
    c) In addition to demographic characteristics, key outcome variables (such as, in an election study, the voter turnout rate and the distribution of votes for a candidate or party) may be poststratification factors for *supplementary* versions of the weights.
    d) Poststratification weighting may be done on two-way marginals (e.g. sex × age) or sets of two-way marginals (e.g. sex × age and sex × race) as well as one-way marginals. A decision to use two-way marginals should be based on a benchmark report that shows discrepancies on those marginals that are not corrected by raking to one-way marginals, or on a desire to optimize the weights for the analysis of a population subgroup.
    e) Before implementing poststratification, employ a simple imputation procedure to replace missing values of demographic variables to be used in the raking only if such a procedure can be implemented readily enough to justify the benefit, which is likely to be slight. If imputation is not implemented, include cases with missing data on raking factors in the dataset and assign them a final weight equal to their nonresponse-adjusted base weight.
    f) If any variables chosen as poststratification factors are continuous or have more than approximately 6 categories or have a category that contains less than approximately 5 percent of the sample, recode each such variable into a categorical variable with no more than 6 categories, none of which contain less than 5 percent of the sample.

5. Rake.
    a) Multiply the nonresponse-adjusted base weight for each case by the factor required to match the target population percentage for the first poststratification factor.
    b) Multiply the product of step *a* by the factor required to match the target population percentage for the next poststratification factor. Continue for each of the remaining poststratification factors.
    c) At each step, cap (truncate) extreme weights, if there are any, to a maximum of about 5 times the mean weight.
    d) Repeat raking until all estimates converge on the benchmarks or until the current iteration produces no change from the previous iteration.
6. After raking, evaluate the raked weights, revise the approach, rake again, and repeat as necessary.
    a) Examine the cases that were capped at item 4d to see if most share a specific characteristic, and raise the cap if this is the case.
    b) After raking, conduct a new benchmark comparison using the new raked weights.
    c) If the benchmark comparison shows that the survey estimates differ from the benchmarks that were used as raking factors, consider increasing weight caps (imposed at item 4d) to 6, 7, or 8.
    d) Examine the effects of raking on variables not used as raking factors. If any of these estimates show a greater difference from the benchmarks using the new weights, try raking with a revised poststratification approach (item 5g).
    e) Examine the coefficient of variation using the new weights, and the design effect using the new weights. If these are greatly inflated (e.g., if the design effect with the new raked weights exceeds the design effect prior to raking by more than 0.5), try raking with a revised poststratification approach to minimize this effect.
    f) Examine the coefficient of variation for the full sample as well as for subsets of interest, such as members of minority groups if the study is intended to allow analyses of these groups.
    g) If revising the poststratification approach: One way to limit the coefficient of variation is to collapse categories in the variables used for raking. Another is to eliminate or replace poststratification factors. A third is to adjust the cap. Increasing the cap can make benchmark estimates more accurate.
    h) If needed, create supplemental weights with greater accuracy.
7. Scale the weights to a mean of 1.000 or to sum to the population size, as desired.

The *anesrake* Package in R

Weight calculations, including raking, can be accomplished by writing code from scratch in any powerful statistical software or by using built-in tools in Stata or WESVAR, or by using user-created modules, programs, or macros developed for Stata (Winter, 2002), SAS (Izrael, Hoaglin, & Battaglia, 2000), or the R statistical programming envornment (Lumley, 2004). However, none of these options is ideal for implementing the procedures described in this paper. Writing code from scratch requires substantial expertise and is very time consuming. Built-in tools in Stata and WESVAR do not implement all of these procedures, and other tools cited above have similar limitations.

The *anesrake* software (Pasek, 2010) is designed to implement the best practices descried above while giving researchers the flexibility to adjust important specifications about the raking procedure. It accomplishes this by presenting a simple interface in *R* whereby researchers can specify base weights as well as a set of targets for weighting and potentially other specifications; the algorithm will then produce weights in line with the proposed best practices. Unlike other available software, *anesrake* is able to automate the selection of variables for weighting, can cap weights at each iteration, rather than only at the end, and will automatically reassess and readjust if initial weights yield new discrepancies for target variables. By default, variables are inserted from most to least discrepant and missing data is handled by ignoring missing cases when raking to a single variable.

anesrake is a package in *R* and can be downloaded from the Comprehensive R Archive Network (CRAN). When calling *anesrake*, users must specify a set of target values (called *inputter*, and formatted as a list in *R*; see example below), a dataset that will be weighted (called *dataframe* and formatted as a data frame in *R*), and a variable specifying unique identifiers for each case (called *caseid* and formatted as a vector).

Additional optional specifications include:

- *weightvec* – a vector of base weights (set to 1 for all individuals if not otherwise specified);
- *cap* – the maximum value for any given weight.
- *type* – a series of options for how variables should be selected for weighting. The default, *type="pctlim"*, will weight on all variables that deviate from their targets by greater than a certain percentage (defined with the command *pctlim=<##>*, where *<##>* is the maximum deviation for variables not selected and defaults to .05). Other options include "*nolim"*, which selects all variables, and *"nlim"*, which selects a specified number of variables with the largest discrepancies.
- *choosemethod* – a series of options for how discrepancies should be defined when variables are selected for weighting. The default, *choosemethod="total"*, will identify the discrepancy as the total error across all categories of a variable. Other options include "average", which will select based on the discrepancy of the average category, or "max" which will select based on the discrepancy of the most discrepant category.
- *filter* – a vector of 1s and 0s indicating what cases should be included for weighting (1=include, 0=exclude). This allows researchers to select the proper data for inclusion (e.g. only individuals who have data on the outcome variable that were present for both waves of a two-wave survey).
- *iterate* – a specification for whether *anesrake* should automatically rerun weighting with additional variables if new discrepancies are produced in the weighting process.

An Example Application

If we wanted to run *anesrake* for the 2004 American National Election Studies panel dataset, we would start by installing the *anesrake* package (if it has not been installed) and loading it into R using the library command:

> *library(anesrake)*

We would then import the data we hope to rake into *R*. In this case, we have already downloaded the data and recoded the demographics we wish to use into categorical variables.

> *load("anes04.rdata")*

This data consists of a data frame called *anes04*, which includes categorical variables for sex, age, education, race/ethnicity, and marital status and a variable with a unique identifier for each case (here named "*caseid")*. The sex variable is named "*sex"* and is coded into categories labeled "*male"* and "*female"*. The age variable is named *"agecats"* and is coded into categories labeled "*age1824"* through "*age6599"*. Other variables have been similarly coded into *factors* (*R*'s term for a categorical variable) with labeled scale points.

After loading the data, researchers need to define the target values for each category. This is accomplished by creating a vector of the target values for each level of each variable; these are then strung together into a *list* element in *R*. To ensure that all variables are weighted to the correct target values, the values for the variables must be named to perfectly match the factor levels in the dataset and the names of the target variables must match the dataset names (note that *R* is case sensitive, so “male” is not the same as “Male”). For sex and age, this looks like the following:

> *> sex <- c(male=.49, female=.51)*
> *> agecats <- c(age1824=.10, age2534=.21, age3544=.19, age4554=.20, age5564=.18, age6599=* .12)

Note that the labels for the target values match those in the data frame; this is how *anesrake* knows what values should be associated with which variables. These variables are then combined to produce a list of targets for *inputter* as follows:

> *> targets <- list(sex, agecats, educcats, raceeth, marital)*

Note again that the names of the variables in the inputter list exactly match the names of the variables in the data frame.

This is sufficient to run the *anesrake* command, which is specified as follows:

> *> anesrake(inputter=targets, dataframe=anes04, caseid=anes04$caseid)*

The algorithm will then examine the target variables, select those with a total discrepancy of greater than 5 percentage points, will run the raking procedure, and will rerun if any additional variables exceed the 5 percentage point threshold. The optional variables can be specified to weight a subset of the dataset (using *filter*) to change the method for choosing variables (*type*) or to set base weights (*weightvec)*. The output of the raking algorithm can be saved to *R*, summarized, or exported as follows:

> *> rakeout <- anesrake(inputter=targets, dataframe=anes04, caseid=anes04$caseid)*
> *> summary(rakeout)*
> > write.csv(print(rakeout), “weights.csv”)

The algorithm will warn users if the raking procedure does not fully converge and the summary can be used to quickly assess how closely the unweighted and weighted data match targets.

Application: anesrake in Practice

The following example briefly illustrates the use of *anesrake* to compute weights for the ANES Time Series datasets from 1994, 1996, 1998, 2000, and 2004. The 2008 dataset was omitted because of its unusual oversample design and the 2012 dataset was omitted because ANES describes the current data as "preliminary" and it is not yet part of the master cumulative data file.

In presidential election years the ANES Time Series survey was a two-wave panel study with a nationally representative sample. The first wave was completed in roughly the two months before the election and the second in roughly the two months after the election. In most years all interviews were conducted face-to-face. In 2000 about half of the interviews were conducted with face-to-face interviewing in respondents' homes and about half were conducted by telephone. In non-presidential election years the survey was one wave after the election. Response rates in all studies exceed 50 percent. We obtained the study data from the "cumulative data file" on the ANES website, www.electionstudies.org. Methodological details concerning the studies are presented there.

Base weights

In each year, we used the number of eligible adults in the sampled household as the base weight. To scale the base weights (so that they had a mean of 1, the number of eligible adults was divided by the average number of eligible adults in the average contacted household in that year. Additional selection probability data were not available on these datasets.

Selecting variables for raking

We used the Current Population Survey from November of each study year for demographic benchmarks. Variables measured comparably on the ANES and November CPS were age, sex, race/ethnicity, educational attainment, marital status, region, and home tenure. We used these variables for raking. In addition, we used the number of children in the household, employment status, voter turnout, vote choice for president, and party vote for Congress as benchmarks when these were available in both datasets. We compared ANES results to CPS estimates for these variables. We set *anesrake* to rake on variables where the largest category differed between the survey and the benchmark by more than three percentage points.

Using anesrake

Before running anesrake the ANES data were recoded into appropriate categories. For example, a variable for age was created where age was broken down into 7 categories: 18-24, 25,-34, 35-44, 45-54, 55-64, 65-74, and 74 and older. Responses such as "refused" and "don't know," which did not fit the demographic categories, were treated as missing data by coding them as "NA".

Annotated *anesrake* code is shown in Appendix A.

Results

In Tables 1 through 3 we summarize the results with the new weights computed with anesrake. Because these weights employ a standardized process, the new weighting strategy can be replicated identically across years of the study, enabling consistent over-time comparisons.

Table 1 shows average discrepancies on variables considered for weighting. Across the 5 studies, the average error on these variables was 2.8 percentage points without the weights, around two percentage points using the base weight (number of eligible household members) or the old weight provided by ANES, and effectively zero using the new weights computed with anesrake. This result demonstrates that the anesrake calculations effectively eliminated discrepancies for the raked variables.

[TABLE 1 HERE]

Table 2 shows average discrepancies on variables not considered for weighting. The average error was 6.2 points for the unweighted data, 6.0 points with the base weight only, 5.5 points with the old weights, and 5.7 points with the new weights. These results demonstrate that the anesrake calculations produce results similar to the study's existing weights and tend to improve on those generated with the unweighted data.

[TABLE 2 HERE]

Table 3 shows general design effects, which averaged 1.18 with the base weight alone, 1.22 with the old weights, and 1.34 with the new weights. These results demonstrate that the anesrake calculations slightly increase the design effect, but that design effects remain low.

[TABLE 3 HERE]

Across these three tables, it is clear that the anesrake weighting program provided results that were an improvement over unweighted and base weighted data for most benchmarks (full results of all comparisons are in Appendix B).

Although the new weighting strategy did not outperform the weights that had previously been provided with the time series datasets, there are considerable reasons to prefer the new weights over the old ones. For one, the old weights represented a diverse set of weighting strategies employed across different years. Because these weights were constructed with a single time series study in mind, they were not technically comparable across years. Further, although the documentation from prior years indicates the variables that were used, information on how those variables were selected is not available. It is possible that the weights provided represent one among many sets of weights that were generated.

Assumptions of the Approach

As with most attempts to correct for some level of survey nonresponse, raking depends fundamentally on the assumption that nonresponse for any given outcome can be treated as Missing At Random (MAR) conditional on a set of covariates. Respondents within each category of each covariate are presumed to mirror nonrespondents for those same categories, *ceteris paribus*. Hence, if there are systematic differences between respondents and nonrespondents, weighting can potentially result in incorrect inferences. To date, however, research has consistently suggested that nonresponse bias is often small (Keeter, Kennedy, Dimock, Best, & Craighill, 2006) and is not closely associated with response rates (Groves & Peytcheva, 2008), which should allay some of these concerns in practice.

Underlying any demographic weighting procedure is an assumption that demographic discrepancies between respondents and the target population represent a threat to inference that is worth correcting. Historically, this approach has been well validated in probability sample surveys, where correcting for demographic discrepancies appears to improve other indicators of accuracy (Yeager et al., 2011). There remain open questions as to whether demographic corrections are sufficient or even helpful for nonprobability samples (Baker et al., 2010; 2013) or for producing estimates of small subpopulations (Gelman, 2007b).

Because there are many approaches to survey weighting, it is valuable to situate raking in the larger context of strategies that researchers can use. Raking is centrally a type of poststratification approach. In this respect, raking has advantages over other poststratification strategies because it can balance a sample across many covariates without radically increasing the variance of the final weights (Kalton & Brick, 1995). When researchers are interested in weighting using many variables, complete poststratification tables typically produce some very large weights in cells where few cases are available. This, in turn, increases the variance of the weights, decreases the effective sample size of the weighted data, and can lead to inferences that are highly dependent on the weights (cf. Elliott & Little, 2000; Kish, 1992).

Other weighting approaches do offer some advantages over raking, but these typically come at the cost of added complexity. Use of calibration methods instead of categorical poststratification would allow for the inclusion of continuous variables, for instance, though it entails other assumptions about the nature of the data (cf. Little, 1993). Propensity score approaches are sometimes more effective than raking approaches, particularly when nonprobability sampling has been used, but they tend to achieve less balance across variables than raking (Deville, Sarndal, & Sautory, 1993). And more complex methods such as Gelman's (2007b) Bayesian approach are more difficult to put into practice, but have the potential to yield even more accurate weights (see e.g. Bell & Cohen, 2007).

Conclusion

The current paper attempts to make the process of survey raking a little less of an art and a little more of a science. By explicating researcher's choices in weighting, proposing clear standards, and providing software for easy implementation, we believe that a broader group of researchers can develop and use weights that are well-suited for their analyses.

In our example using the ANES, it is not surprising that that the new weights are more accurate for characteristics indicated. The new weights rake on more variables, so this result is to be expected, and does not indicate that the old weights were poor. The problem with extant weighting is not that it is poorly done, but that it is hard for most researchers to do, it is not done using consistent methods, and the methods used are not as transparent as they could be. The new procedure has the advantages of improved accessibility, transparency, and consistency.

References

Baker, R., Blumberg, S. J., Brick, J. M., Couper, M. P., Courtright, M., Dennis, J. M., et al. (2010). AAPOR Report on Online Panels. *Public Opinion Quarterly*, *74*(4), 711–781. doi:10.1093/poq/nfq048

Baker, R., Brick, J. M., Bates, N. A., Battaglia, M. P., Couper, M. P., Dever, J. A., et al. (2013). Summary Report of the AAPOR Task Force on Non-probability Sampling. *Journal of Survey Statistics and Methodology*, *1*(2), 90–143. Retrieved from http://www.aapor.org/AM/Template.cfm?Section=Reports1&Template=/CM/ContentDisplay.cfm&ContentID=5963

Bell, R. M., & Cohen, M. L. (2007). Comment: Struggles with Survey Weighting and Regression Modeling. *Statistical Science*, *22*(2), 165–167.

Bethlehem, J. G. (2001). Weighting Nonresponse Adjustments Based on Auxiliary Information. In R. M. Groves, D. A. Dillman, J. L. Eltinge, & R. J. A. Little, *Survey Nonresponse*. New York: John Wiley and Sons.

Blair, J., Czaja, R. F., & Blair, E. A. (2013). *Designing Surveys*. SAGE Publications, Incorporated.

Breidt, F. J., & Opsomer, J. D. (2007). Comment: Struggles with Survey Weighting and Regression Modeling. *Statistical Science*, *22*(2), 168–170. doi:10.1214/088342307000000195

Campbell, J. E. (2010). Explaining Politics, Not Polls: Reexamining Macropartisanship with Recalibrated NES Data. *Public Opinion Quarterly*, *74*(4), 616–642. doi:10.1093/poq/nfq042

Darroch, J. N., & Ratcliff, D. (1972). Generalized Iterative Scaling for Log-Linear Models. *The Annals of Mathematical Statistics*, *43*(5), 1470–1480.

DeBell, M., & Krosnick, J. A. (2009). *Computing Weights for American National Election Study*

Survey Data (No. nes012427). Ann Arbor, MI, and Palo Alto, CA: ANES Technical Report series.

Deming, W. E., & Stephan, F. F. (1940). On a Least Squares Adjustment of a Sampled Frequency Table When the Expected Marginal Totals are Known. *The Annals of Mathematical Statistics*, *11*(4), 427–444.

Deville, J.-C., Sarndal, C.-E., & Sautory, O. (1993). Generalized Raking Procedures in Survey Sampling. *Journal of the American Statistical Association*, *88*(423), 1013–1020.

Dorofeev, S., & Grant, P. (2006). *Statistics for Real-Life Sample Surveys*. Cambridge University Press.

Elliott, M. R., & Little, R. J. A. (2000). Model-based alternatives to trimming survey weights. *Journal of Official Statistics*, *16*(3), 191–210.

Fienberg, S. E. (1970). An Iterative Procedure for Estimation in Contingency Tables. *The Annals of Mathematical Statistics*, *41*(3), 907–917.

Fink, A. (2009). *How to Conduct Surveys: A Step-by-step Guide*. Thousand Oaks, CA: Sage.

Gelman, A. (2007a). Rejoinder: Struggles with Survey Weighting and Regression Modeling. *Statistical Science*, *22*(2), 184–188.

Gelman, A. (2007b). Struggles with Survey Weighting and Regression Modeling. *Statistical Science*, *22*(2), 153–164.

Gelman, A., & Carlin, J. B. (2002). Poststratification and Weighting Adjustments. In R. M. Groves, D. A. Dillman, J. L. Eltinge, & R. J. A. Little, *Survey Nonresponse*. New York: John Wiley and Sons.

Groves, R. M., & Peytcheva, E. (2008). The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis. *Public Opinion Quarterly*, *72*(2), 167–189. doi:10.1093/poq/nfn011

Groves, R. M., Floyd J Fowler, J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R.

(2009). *Survey Methodology* (2nd ed.). John Wiley & Sons.

Horvitz, D. G., & Thompson, D. J. (1952). A Generalization of Sampling Without Replacement From a Finite Universe. *Journal of the American Statistical Association*, *47*(260), 663–685. doi:10.2307/2280784

Ireland, C. T., & Kullback, S. (1968). Contingency tables with given marginals. *Biometrika*, *55*(1), 179–188. doi:10.1093/biomet/55.1.179

Izrael, D., Hoaglin, D. C., & Battaglia, M. P. (2000). A SAS macro for balancing a weighted sample (pp. 1350–1355). Presented at the Proceedings of the Twenty-Fifth Annual SAS Users Group International Conference.

Kalton, G., & Brick, J. M. (1995). Weighting schemes for household panel surveys. *Survey Methodology*.

Keeter, S., Kennedy, C., Dimock, M., Best, J., & Craighill, P. (2006). Gauging the impact of growing nonresponse on estimates from a national RDD telephone survey. *Public Opinion Quarterly*, *70*(5), 759–779.

Kish, L. (1965). *Survey sampling*. New York: John Wiley & Sons.

Kish, L. (1992). Weighting for unequal P i. *Journal of Official Statistics*, *8*(2), 183–200.

Lee, S., & Valliant, R. (2008). Weighting Telephone Samples Using Propensity Scores. In J. M. Lepkowski, C. Tucker, J. M. Brick, E. D. de Leeuw, L. Japec, P. J. Lavrakas, et al., *Advances in Telephone Survey Methodology* (pp. 170–185). Hoboken, NJ: John Wiley and Sons.

Little, R. J. A. (1993). Post-Stratification: A Modeler's Perspective. *Journal of the American Statistical Association*, *88*(423), 1001–1012. doi:10.2307/2290792

Lohr, S. (2009). *Sampling: Design and Analysis* (2nd ed.). Cengage Learning.

Lumley, T. (2004). Analysis of complex survey samples. *Journal of Statistical Software*, *9*(1), 1–19.

Michalos, A. C., & Orlando, J. A. (2006). Quality of Life of Some Under-Represented Survey

Respondents: Youth, Aboriginals and Unemployed. *Social Indicators Research*, *79*(2), 191–213. doi:10.1007/s11205-005-4717-2

Pasek, J. (2010). Package "anesrake," 778.

Pasek, J., DeBell, M., & Krosnick, J. A. (2010). Toward a Standardization of Survey Weights: The American National Election Studies Weighting System. Presented at the Annual Meeting of the American Association for Public Opinion Research, Chicago.

Rea, L. M., & Parker, R. A. (1992). *Designing and Conducting Survey Research*. John Wiley & Sons.

Smith, T. W., & Stephenson, C. B. (1979). *An Analysis of Test/Retest Experiments on the 1972, 1973, 1974, and 1978 General Social Surveys* (No. 8). *publicdata.norc.org*. Chicago: GSS Methodological Report.

Valliant, R., Dever, J. A., & Kreuter, F. (2013). *Practical Tools for Designing and Weighting Survey Samples*. New York: Springer.

Voss, D. S., Gelman, A., & King, G. (1995). A Review: Preelection Survey Methodology: Details From Eight Polling Organizations, 1988 and 1992. *Public Opinion Quarterly*, *59*(1), 98–132.

Winter, N. (2002). SURVWGT: Stata module to create and manipulate survey weights. *Statistical Software Components*.

Yeager, D. S., Krosnick, J. A., Chang, L., Javitz, H. S., Levendusky, M. S., Simpser, A., & Wang, R. (2011). Comparing the Accuracy of RDD Telephone Surveys and Internet Surveys Conducted with Probability and Non-Probability Samples. *Public Opinion Quarterly*, *75*(4), 709–747. doi:10.1093/poq/nfr020

Table 1. Average discrepancies on variables considered for weighting

Year	Unweighted	Base weight only	Old weight	New weight
1994	2.4%	1.7%	1.5%	0.1%
1996	2.8%	2.8%	2.0%	0.0%
1998	2.7%	2.4%	2.0%	0.0%
2000	3.0%	2.3%	1.9%	0.0%
2004	2.9%	2.5%	2.0%	0.1%
Average	***2.8%***	***2.3%***	***1.9%***	***0.1%***

Table 2. Average discrepancies on variables *not* considered for weighting

Year	Unweighted	Base weight only	Old weight	New weight	# Unweighted Benchmarks
1994	6.7%	6.3%	5.9%	5.5%	8
1996	7.2%	7.4%	6.0%	6.9%	9
1998	8.2%	8.2%	7.6%	9.3%	6
2000	5.9%	5.2%	5.5%	4.9%	11
2004	4.8%	4.7%	4.3%	4.3%	16
Wtd. Average	***6.2%***	***6.0%***	***5.5%***	***5.7%***	

Table 3. General design effects (coefficient of variation)

Year	Unweighted	Base weight only	Old weight	New weight
1994	1.00	1.17	1.23	1.27
1996	1.00	1.17	1.26	1.39
1998	1.00	1.24	1.18	1.35
2000	1.00	1.16	1.24	1.36
2004	1.00	1.17	1.21	1.33
Average	***1.00***	***1.18***	***1.22***	***1.34***

Appendix A – Annotated Replication Code For Raking ANES Data (only 2004 shown)

 # Load required packages for weighting data

> library(foreign) #for importing data
> library(weights) #for producing simple weighted statistics
> library(anesrake) #for running anesrake

 # Load CPS data for 2004

> load("Data/CPSRFiles/cpsnov04.Rdata")
dataset is named nov04

 # Create dataset with relevant CPS variables for targets

> cpsmerged <- with(nov04, data.frame(yr=2004, tenure=hetenure, hhnum=hrnumhou, numownkids=prnmchld, region=gereg, age=prtage, marital=pemaritl, psex=pesex, educ=peeduca, race=ptdtrace, hispanic=pehspnon, born=penatvty, mbirthpl=pemntvty, fbirthpl=pefntvty, cship=prcitshp, employ=prempnot, registered=pes2, faminc=hufaminc, weight=pwsswgt))

 # Recode CPS variables to categories that will match those in 2004 ANES
The first line takes "tenure" variable and recodes it into "homeown" with categories "Owner" and "NonOwner"

> cpsmerged$homeown <- cut(cpsmerged$tenure, c(0, 1.5, 3.5), c("Owner", "NonOwner"))
> cpsmerged$cregion <- factor(cpsmerged$region, 1:4, c("Northeast", "Midwest", "South", "West"))
> cpsmerged$agecats <- cut(cpsmerged$age, breaks=c(17.5, 24.5, 34.5, 44.5, 54.5, 64.5, 74.5, 99), cpsmerged$labels=c("age1824", "age2534", "age3544", "age4554", "age5564", "age6574", "age75up"))
> cpsmerged$married <- cut(cpsmerged$marital, c(0, 2.5, 5.5, 6.5), c("Married", "Unmarried", "NeverMarried"))
> cpsmerged$sex <- factor(cpsmerged$psex, 1:2, c("Male", "Female"))
> cpsmerged$educcat <- cut(cpsmerged$educ, c(30, 38.5, 39.5, 42.5, 43.5, 47), c("LessThanHS", "HSGrad", "SomeCol", "CollegeGrad", "AdvancedDegree"))

> raceeth <- cut(cpsmerged$race, c(0, 1.5, 2.5, 5, 6), c("WhiteNH", "BlackNH", "OtherMultipleNH", "Hispanic"))
> raceeth[cpsmerged$hispanic==1] <- "Hispanic"

 # Combine target variables into dataset with only citizens aged 18 or older

> cpsused <- with(cpsmerged[cpsmerged$age>18 & cpsmerged$citizen=="Citizen" & cpsmerged$weight>0 & cpsmerged$yr==y,], data.frame(homeown=homeown, region=cregion, agecats=agecats, married=married, sex=sex, educcats=educcat, raceeth=raceeth, weight=weight/mean(weight))

 # Generate target proportions of US citizens age 18 or older who are in each CPS category

*> cpstargs <- lapply(*cpsused*, function(x) wpct(x, cpstargs $weight)))*

 # Show what targets look like

> cpstargs

```
$homeown
   Owner  NonOwner
0.7100801 0.2899199

$region
Northeast   Midwest     South      West
0.1966221 0.2496866 0.3585141 0.1951772

$agecats
   age1824    age2534    age3544    age4554    age5564    age6574    age75up
0.11525611 0.21683627 0.22269129 0.16357607 0.11086137 0.10018027 0.07059862

$married
    Married    Unmarried NeverMarried
  0.5920694    0.1962603    0.2116703

$sex
    Male    Female
0.4764973 0.5235027

$educcats
   LessThanHS       HSGrad       SomeCol    CollegeGrad AdvancedDegree
   0.16110486    0.34948633    0.27762747     0.14535138     0.06642996

$raceeth
      WhiteNH       BlackNH OtherMultipleNH       Hispanic
    0.81899930    0.11846199      0.01367144     0.04886728
```

 # Import ANES data

> nesall <- read.dta("Data/ANES/anes_cdf.dta")

 # Restrict to 2004 data

> nesall$year <- nesall$VCF0004
> nes <- nesall[nesall$year==2004,]

 # Define unique identifier for each case

> nes$caseid <- nes$VCF0006a

 # Calculate base weight

```
> nes$eligible <- as.numeric(nes$VCF9122)
> nes$basewt <- (nes$eligible)/mean(nes$eligible, na.rm=TRUE)
```

 # Recode variables into variable names and category levels that match those in targets
Note that r is case-sensitive so both the names of the variables and the levels must match perfectly for it to work

```
> nes$sex <- nes$VCF0104
> levels(nes$sex) <- c(NA, "Male", "Female")
> nes$agecats <- cut(nes$VCF0101, breaks=c(17.5, 24.5, 34.5, 44.5, 54.5, 64.5, 74.5, 99.5),
labels=c("age1824", "age2534", "age3544", "age4554", "age5564", "age6574", "age75up"))
> nes$raceeth <- factor(nes$VCF0106, 1:4, c("WhiteNH", "BlackNH", "OtherMultipleNH",
"Hispanic"))
> nes$raceeth[nes$VCF0108=="1. Yes, R is Hispanic"] <- "Hispanic"
> nes$region <- nes$VCF0112
> levels(nes$region) <- c(NA, "Northeast", "Midwest", "South", "West")
> nes$educcats <- cut(as.numeric(nes$VCF0140a), c(0, 2.5, 3.5, 5.5, 6.5, 7.5),
labels=c("LessThanHS", "HSGrad", "SomeCol", "CollegeGrad", "AdvancedDegree"))
> nes$homeown <- factor(as.numeric(nes$VCF0146=="1. Yes, own"), levels=0:1,
c("NonOwner", "Owner"))
> nes$homeown[nes$V001022 %in% c("8. DK", "9. NA; RF; no Pre IW; short form (1992)")] <-
NA
> nes$married <- factor((nes$VCF0147== "1. Married")+2*(nes$VCF0147=="2. Never
married"), levels=0:2, c("Unmarried", "Married", "NeverMarried"))
> nes$married[nes$VCF0147 %in% c("0. NA", "8. DK", "9. NA; no Pre IW; unmarried at time of
IW (1952 only);")] <- NA
```

 # Look at relevant variables in ANES to see that the variables and categories match those of the targets

```
> summary(nes)
```

 # Run weighting algorithm

```
> wtout <- anesrake(weighttargs, dataframe=nes, nes$caseid, weightvec=nes$basewt, pctlim=3,
choosemethod="max")
```

choosemethod="max" uses largest discrepancy category for each variable to determine whether to weight on each variable
pctlim sets the size of the discrepancy to 3 percentage points for deciding to select a variable

new weights are accessible by typing: wtout$weightvec

 # Summarize results of weighting process:

```
> summary(wtout)
```

Table B1 - Variables Considered for Raking 1994

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Sex - Male	47.6%	46.6%	1.1%	48.5%	-0.9%	47.9%	-0.2%	48.2%	-0.6%
Sex - Female	52.4%	53.4%	-1.1%	51.5%	0.9%	52.1%	0.2%	51.8%	0.6%
Age Category - age1824	11.5%	8.9%	2.7%	11.3%	0.3%	13.0%	-1.5%	11.5%	0.0%
Age Category - age2534	21.7%	21.9%	-0.2%	21.0%	0.7%	22.0%	-0.3%	21.7%	0.0%
Age Category - age3544	22.3%	23.3%	-1.1%	23.4%	-1.1%	22.7%	-0.4%	22.3%	0.0%
Age Category - age4554	16.4%	14.3%	2.1%	15.2%	1.2%	14.8%	1.6%	16.4%	0.0%
Age Category - age5564	11.1%	11.3%	-0.2%	11.4%	-0.3%	10.8%	0.3%	11.1%	0.0%
Age Category - age6574	10.0%	12.6%	-2.6%	11.8%	-1.8%	10.9%	-0.9%	10.0%	0.0%
Age Category - age75up	7.1%	7.7%	-0.7%	5.9%	1.1%	5.8%	1.2%	7.1%	0.0%
Education - LessThanHS	16.1%	15.9%	0.2%	15.2%	1.0%	19.2%	-3.1%	16.1%	0.0%
Education - HSGrad	34.9%	33.1%	1.9%	34.6%	0.3%	34.9%	0.0%	34.9%	0.0%
Education - SomeCol	27.8%	25.6%	2.2%	25.4%	2.4%	25.4%	2.4%	27.8%	0.0%
Education - CollegeGrad	14.5%	17.5%	-3.0%	17.3%	-2.8%	14.3%	0.2%	14.5%	0.0%
Education - AdvancedDegree	6.6%	8.0%	-1.3%	7.6%	-0.9%	6.1%	0.5%	6.6%	0.0%
Census Region - Northeast	19.7%	15.0%	4.6%	14.9%	4.8%	16.7%	3.0%	19.7%	0.0%
Census Region - Midwest	25.0%	27.5%	-2.5%	28.0%	-3.0%	27.1%	-2.2%	25.0%	0.0%
Census Region - South	35.9%	36.9%	-1.0%	37.2%	-1.3%	36.9%	-1.1%	35.9%	0.0%
Census Region - West	19.5%	20.6%	-1.1%	20.0%	-0.5%	19.2%	0.3%	19.5%	0.0%
Home Ownership Status - NonOwner	29.0%	32.1%	-3.1%	28.4%	0.6%	30.9%	-1.9%	29.7%	-0.7%
Home Ownership Status - Owner	71.0%	67.9%	3.1%	71.6%	-0.6%	69.1%	1.9%	70.3%	0.7%
Marital Status - Unmarried	19.6%	28.1%	-8.5%	20.6%	-0.9%	21.3%	-1.7%	19.6%	0.0%
Marital Status - Married	59.2%	52.8%	6.4%	61.3%	-2.1%	58.9%	0.3%	59.2%	0.0%
Marital Status - Never Married	21.2%	19.1%	2.1%	18.1%	3.1%	19.8%	1.4%	21.2%	0.0%
Race/Ethnicity - WhiteNH	81.9%	76.7%	5.2%	76.9%	5.0%	74.7%	7.2%	81.9%	0.0%
Race/Ethnicity - BlackNH	11.8%	11.2%	0.7%	10.4%	1.5%	11.6%	0.2%	11.8%	0.0%
Race/Ethnicity - OtherMultipleNH	1.4%	3.9%	-2.5%	4.2%	-2.8%	4.2%	-2.8%	1.4%	0.0%
Race/Ethnicity - Hispanic	4.9%	8.3%	-3.4%	8.6%	-3.7%	9.5%	-4.6%	4.9%	0.0%
Average Absolute Discrepancy			2.4%		1.7%		1.5%		0.1%

Table B2 - Variables NOT Considered for Raking 1994

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Employment Status - Not Employed	34.8%	37.4%	-2.6%	36.0%	-1.2%	36.5%	-1.8%	35.5%	-0.7%
Employment Status - Employed	65.2%	62.6%	2.6%	64.0%	1.2%	63.5%	1.8%	64.5%	0.7%
Both Parents Born in US	10.6%	16.3%	-5.8%	16.3%	-5.7%	16.9%	-6.3%	14.4%	-3.8%
Parents Not Both Born in US	89.4%	83.7%	5.8%	83.7%	5.7%	83.1%	6.3%	85.6%	3.8%
Turnout Status - Nonvoter	58.9%	41.3%	17.6%	40.7%	18.2%	44.3%	14.6%	41.6%	17.3%
Turnout Status - Voted	41.1%	58.7%	-17.6%	59.3%	-18.2%	55.7%	-14.6%	58.4%	-17.3%
Vote Choice for Congress - Democrat	46.5%	47.1%	-0.7%	46.4%	0.1%	47.4%	-1.0%	46.5%	0.0%
Vote Choice for Congress - Republican	53.5%	52.9%	0.7%	53.6%	-0.1%	52.6%	1.0%	53.5%	0.0%
Average Absolute Discrepancy			6.7%		6.3%		5.9%		5.5%

Table B3 - Variables Considered for Raking 1996

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Sex - Male	47.6%	44.8%	2.8%	46.1%	1.6%	45.6%	2.0%	47.0%	0.6%
Sex - Female	52.4%	55.2%	-2.8%	53.9%	-1.6%	54.4%	-2.0%	53.0%	-0.6%
Age Category - age1824	11.1%	6.8%	4.3%	5.3%	5.8%	12.0%	-0.9%	11.1%	0.0%
Age Category - age2534	20.5%	19.4%	1.1%	19.0%	1.5%	21.3%	-0.7%	20.5%	0.0%
Age Category - age3544	22.6%	24.5%	-1.9%	25.1%	-2.5%	22.7%	-0.1%	22.6%	0.0%
Age Category - age4554	17.4%	15.9%	1.5%	15.7%	1.7%	15.7%	1.7%	17.4%	0.0%
Age Category - age5564	11.1%	13.0%	-1.8%	13.5%	-2.4%	11.8%	-0.7%	11.1%	0.0%
Age Category - age6574	9.8%	11.9%	-2.0%	12.1%	-2.3%	10.0%	-0.2%	9.8%	0.0%
Age Category - age75up	7.4%	8.6%	-1.1%	9.2%	-1.8%	6.4%	1.0%	7.4%	0.0%
Education - LessThanHS	15.2%	13.4%	1.8%	13.9%	1.4%	18.3%	-3.0%	15.2%	0.0%
Education - HSGrad	34.8%	32.0%	2.7%	31.4%	3.3%	33.3%	1.4%	34.8%	0.0%
Education - SomeCol	27.6%	27.1%	0.5%	26.3%	1.3%	26.7%	0.9%	27.6%	0.0%
Education - CollegeGrad	15.3%	17.9%	-2.6%	18.4%	-3.1%	14.2%	1.1%	15.3%	0.0%
Education - AdvancedDegree	7.1%	9.6%	-2.5%	10.0%	-2.8%	7.5%	-0.4%	7.1%	0.0%
Census Region - Northeast	19.1%	15.2%	3.9%	14.9%	4.2%	16.1%	3.0%	19.1%	0.0%
Census Region - Midwest	25.0%	26.7%	-1.8%	27.4%	-2.4%	26.4%	-1.5%	25.0%	0.0%
Census Region - South	36.5%	37.5%	-0.9%	37.2%	-0.6%	38.4%	-1.8%	36.5%	0.0%
Census Region - West	19.5%	20.7%	-1.2%	20.6%	-1.1%	19.2%	0.3%	19.5%	0.0%
Home Ownership Status - NonOwner	27.6%	31.8%	-4.2%	30.5%	-2.9%	32.0%	-4.4%	27.6%	0.0%
Home Ownership Status - Owner	72.4%	68.2%	4.2%	69.5%	2.9%	68.0%	4.4%	72.4%	0.0%
Marital Status - Unmarried	19.8%	27.4%	-7.7%	27.4%	-7.7%	20.6%	-0.8%	19.8%	0.0%
Marital Status - Married	59.0%	54.3%	4.7%	55.5%	3.5%	58.8%	0.1%	59.0%	0.0%
Marital Status - Never Married	21.3%	18.3%	3.0%	17.1%	4.2%	20.6%	0.7%	21.3%	0.0%
Race/Ethnicity - WhiteNH	81.3%	74.1%	7.3%	75.0%	6.4%	71.1%	10.2%	81.3%	0.0%
Race/Ethnicity - BlackNH	11.9%	11.8%	0.1%	11.1%	0.7%	12.5%	-0.6%	11.9%	0.0%
Race/Ethnicity - OtherMultipleNH	1.7%	5.4%	-3.8%	5.6%	-4.0%	6.1%	-4.5%	1.7%	0.0%
Race/Ethnicity - Hispanic	5.1%	8.7%	-3.6%	8.2%	-3.1%	10.3%	-5.2%	5.1%	0.0%
Average Absolute Discrepancy			2.8%		2.8%		2.0%		0.0%

Table B4 - Variables NOT Considered for Raking 1996

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Employment Status - Not Employed	34.4%	36.2%	-1.8%	36.0%	-1.6%	34.8%	-0.4%	33.8%	0.6%
Employment Status - Employed	65.6%	63.8%	1.8%	64.0%	1.6%	65.2%	0.4%	66.2%	-0.6%
Turnout Status - Nonvoter	48.3%	23.4%	24.9%	22.4%	25.9%	27.1%	21.2%	23.7%	24.6%
Turnout Status - Voted	51.7%	76.6%	-24.9%	77.6%	-25.9%	72.9%	-21.2%	76.3%	-24.6%
Vote Choice for Congress - Democrat	50.2%	48.3%	1.9%	47.4%	2.8%	48.8%	1.4%	47.0%	3.2%
Vote Choice for Congress - Republican	49.8%	51.7%	-1.9%	52.6%	-2.8%	51.2%	-1.4%	53.0%	-3.2%
Vote Choice for President - Democrat	49.2%	52.9%	-3.7%	52.3%	-3.2%	53.1%	-3.9%	51.6%	-2.5%
Vote Choice for President - Republican	40.7%	38.3%	2.4%	39.5%	1.1%	37.8%	2.9%	39.0%	1.7%
Vote Choice for President - Other	10.2%	8.8%	1.3%	8.1%	2.0%	9.1%	1.0%	9.4%	0.8%
Average Absolute Discrepancy			7.2%		7.4%		6.0%		6.9%

Table B5 - Variables Considered for Raking 1998

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Sex - Male	47.8%	44.9%	2.9%	47.2%	0.6%	45.8%	2.0%	47.8%	0.0%
Sex - Female	52.2%	55.1%	-2.9%	52.8%	-0.6%	54.2%	-2.0%	52.2%	0.0%
Age Category - age1824	11.0%	12.1%	-1.1%	15.9%	-4.8%	13.3%	-2.3%	11.0%	0.0%
Age Category - age2534	19.1%	16.3%	2.8%	15.5%	3.6%	17.2%	1.9%	19.1%	0.0%
Age Category - age3544	22.7%	24.7%	-2.0%	24.1%	-1.4%	24.1%	-1.4%	22.7%	0.0%
Age Category - age4554	18.1%	18.2%	-0.1%	18.0%	0.1%	17.2%	0.9%	18.1%	0.0%
Age Category - age5564	11.9%	12.3%	-0.4%	12.2%	-0.4%	12.0%	-0.1%	11.9%	0.0%
Age Category - age6574	9.5%	8.6%	0.9%	8.2%	1.3%	8.6%	1.0%	9.5%	0.0%
Age Category - age75up	7.7%	7.8%	-0.1%	6.0%	1.7%	7.8%	-0.1%	7.7%	0.0%
Education - LessThanHS	14.3%	13.2%	1.1%	12.7%	1.6%	16.0%	-1.6%	14.3%	0.0%
Education - HSGrad	34.2%	30.3%	3.9%	29.3%	4.9%	34.0%	0.2%	34.2%	0.0%
Education - SomeCol	28.1%	28.7%	-0.6%	30.2%	-2.1%	27.5%	0.6%	28.1%	0.0%
Education - CollegeGrad	15.8%	16.7%	-0.9%	16.2%	-0.4%	13.8%	2.0%	15.8%	0.0%
Education - AdvancedDegree	7.5%	11.1%	-3.6%	11.6%	-4.0%	8.7%	-1.2%	7.5%	0.0%
Census Region - Northeast	18.8%	16.5%	2.2%	15.8%	3.0%	18.7%	0.1%	18.8%	0.0%
Census Region - Midwest	24.9%	26.2%	-1.3%	25.3%	-0.4%	24.7%	0.2%	24.9%	0.0%
Census Region - South	36.6%	36.6%	0.0%	39.0%	-2.4%	37.5%	-0.9%	36.6%	0.0%
Census Region - West	19.7%	20.6%	-0.9%	19.9%	-0.2%	19.1%	0.6%	19.7%	0.0%
Home Ownership Status - NonOwner	26.5%	34.4%	-7.9%	33.1%	-6.6%	32.2%	-5.7%	26.5%	0.0%
Home Ownership Status - Owner	73.5%	65.6%	7.9%	66.9%	6.6%	67.8%	5.7%	73.5%	0.0%
Marital Status - Unmarried	19.8%	25.9%	-6.1%	19.8%	0.0%	20.3%	-0.5%	19.8%	0.0%
Marital Status - Married	58.3%	53.0%	5.3%	58.9%	-0.5%	59.7%	-1.4%	58.3%	0.0%
Marital Status - Never Married	21.9%	21.1%	0.8%	21.4%	0.5%	20.0%	1.9%	21.9%	0.0%
Race/Ethnicity - WhiteNH	81.0%	72.8%	8.2%	73.0%	8.0%	72.1%	8.9%	81.0%	0.0%
Race/Ethnicity - BlackNH	11.9%	11.6%	0.3%	10.8%	1.2%	11.4%	0.5%	11.9%	0.0%
Race/Ethnicity - OtherMultipleNH	1.8%	4.7%	-2.9%	4.6%	-2.8%	4.6%	-2.8%	1.8%	0.0%
Race/Ethnicity - Hispanic	5.3%	10.8%	-5.5%	11.6%	-6.3%	11.9%	-6.6%	5.3%	0.0%
Average Absolute Discrepancy			2.7%		2.4%		2.0%		0.0%

Table B6 - Variables NOT Considered for Raking 1996

	Target	Unweighted		Base Weighted		Old Weight		New Weight	
		Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Employment Status - Not Employed	33.5%	42.3%	-8.8%	43.0%	-9.4%	43.0%	-9.5%	43.6%	-10.0%
Employment Status - Employed	66.5%	57.7%	8.8%	57.0%	9.4%	57.0%	9.5%	56.4%	10.0%
Turnout Status - Nonvoter	60.7%	46.2%	14.5%	47.6%	13.1%	47.9%	12.8%	46.4%	14.3%
Turnout Status - Voted	39.3%	53.8%	-14.5%	52.4%	-13.1%	52.1%	-12.8%	53.6%	-14.3%
Vote Choice for Congress - Democrat	49.5%	48.0%	1.5%	47.3%	2.2%	49.1%	0.4%	46.1%	3.4%
Vote Choice for Congress - Republican	50.5%	52.0%	-1.5%	52.7%	-2.2%	50.9%	-0.4%	53.9%	-3.4%
Average Absolute Discrepancy			8.2%		8.2%		7.6%		9.3%

Table B7 - Variables Considered for Raking 2000

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Sex - Male	47.6%	43.7%	3.9%	44.8%	2.8%	43.9%	3.7%	47.6%	0.0%
Sex - Female	52.4%	56.3%	-3.9%	55.2%	-2.8%	56.1%	-3.7%	52.4%	0.0%
Age Category - age1824	11.5%	8.1%	3.3%	10.3%	1.1%	12.7%	-1.2%	11.5%	0.0%
Age Category - age2534	17.9%	17.0%	0.9%	16.7%	1.1%	17.3%	0.6%	17.9%	0.0%
Age Category - age3544	22.1%	24.0%	-1.9%	23.8%	-1.6%	23.1%	-0.9%	22.1%	0.0%
Age Category - age4554	19.2%	18.7%	0.5%	19.9%	-0.7%	17.1%	2.1%	19.2%	0.0%
Age Category - age5564	12.2%	14.6%	-2.4%	14.2%	-2.0%	12.9%	-0.6%	12.2%	0.0%
Age Category - age6574	9.3%	9.6%	-0.3%	8.8%	0.5%	9.5%	-0.3%	9.3%	0.0%
Age Category - age75up	7.9%	7.9%	0.0%	6.4%	1.5%	7.4%	0.4%	7.9%	0.0%
Education - LessThanHS	13.1%	10.0%	3.1%	9.8%	3.2%	15.0%	-1.9%	13.1%	0.0%
Education - HSGrad	33.8%	28.8%	5.0%	29.1%	4.7%	33.3%	0.6%	33.8%	0.0%
Education - SomeCol	29.0%	30.3%	-1.3%	30.8%	-1.8%	28.1%	0.9%	29.0%	0.0%
Education - CollegeGrad	16.3%	20.7%	-4.4%	20.5%	-4.1%	16.1%	0.2%	16.3%	0.0%
Education - AdvancedDegree	7.8%	10.2%	-2.4%	9.8%	-2.0%	7.6%	0.2%	7.8%	0.0%
Census Region - Northeast	18.6%	17.5%	1.2%	16.7%	2.0%	19.4%	-0.7%	18.6%	0.0%
Census Region - Midwest	24.8%	24.9%	-0.1%	25.7%	-0.9%	24.7%	0.1%	24.8%	0.0%
Census Region - South	36.7%	36.4%	0.3%	36.5%	0.2%	35.7%	0.9%	36.7%	0.0%
Census Region - West	19.9%	21.3%	-1.3%	21.2%	-1.3%	20.2%	-0.3%	19.9%	0.0%
Home Ownership Status - NonOwner	25.2%	32.9%	-7.7%	29.0%	-3.8%	31.7%	-6.5%	25.2%	0.0%
Home Ownership Status - Owner	74.8%	67.1%	7.7%	71.0%	3.8%	68.3%	6.5%	74.8%	0.0%
Marital Status - Unmarried	19.9%	28.5%	-8.6%	21.6%	-1.7%	22.5%	-2.6%	19.9%	0.0%
Marital Status - Married	57.8%	52.1%	5.7%	59.8%	-2.0%	57.2%	0.6%	57.8%	0.0%
Marital Status - Never Married	22.3%	19.4%	2.9%	18.6%	3.7%	20.3%	2.0%	22.3%	0.0%
Race/Ethnicity - WhiteNH	80.5%	74.9%	5.6%	74.9%	5.6%	73.4%	7.1%	80.5%	0.0%
Race/Ethnicity - BlackNH	12.2%	11.6%	0.6%	11.7%	0.5%	12.3%	0.0%	12.2%	0.0%
Race/Ethnicity - OtherMultipleNH	1.7%	6.1%	-4.3%	6.2%	-4.4%	6.0%	-4.3%	1.7%	0.0%
Race/Ethnicity - Hispanic	5.5%	7.5%	-2.0%	7.2%	-1.7%	8.3%	-2.8%	5.5%	0.0%
Average Absolute Discrepancy			3.0%		2.3%		1.9%		0.0%

Table B8 - Variables NOT Considered for Raking 2000

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Employment Status - Not Employed	33.7%	35.7%	-2.1%	34.5%	-0.8%	37.2%	-3.5%	36.4%	-2.7%
Employment Status - Employed	66.3%	64.3%	2.1%	65.5%	0.8%	62.8%	3.5%	63.6%	2.7%
Both Parents Born in US	9.2%	15.0%	-5.8%	14.3%	-5.1%	15.1%	-5.9%	13.0%	-3.8%
Parents Not Both Born in US	90.8%	85.0%	5.8%	85.7%	5.1%	84.9%	5.9%	87.0%	3.8%
Turnout Status - Nonvoter	44.7%	23.9%	20.8%	23.4%	21.3%	27.3%	17.4%	25.0%	19.7%
Turnout Status - Voted	55.3%	76.1%	-20.8%	76.6%	-21.3%	72.7%	-17.4%	75.0%	-19.7%
Vote Choice for Congress - Democrat	49.8%	51.3%	-1.4%	50.3%	-0.5%	51.4%	-1.6%	50.3%	-0.5%
Vote Choice for Congress - Republican	50.2%	48.7%	1.4%	49.7%	0.5%	48.6%	1.6%	49.7%	0.5%
Vote Choice for President - Democrat	48.3%	50.6%	-2.3%	49.1%	-0.8%	49.9%	-1.7%	48.6%	-0.3%
Vote Choice for President - Republican	47.8%	45.5%	2.3%	47.2%	0.6%	46.1%	1.7%	47.8%	0.0%
Vote Choice for President - Other	3.9%	3.9%	0.1%	3.8%	0.1%	4.0%	0.0%	3.6%	0.3%
Average Absolute Discrepancy			5.9%		5.2%		5.5%		4.9%

Table B9 - Variables Considered for Raking 2004

	Target	Unweighted		Base Weighted		Old Weight		New Weight	
		Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
Sex - Male	47.7%	46.7%	1.0%	48.6%	-0.9%	48.5%	-0.8%	49.2%	-1.5%
Sex - Female	52.3%	53.3%	-1.0%	51.4%	0.9%	51.5%	0.8%	50.8%	1.5%
Age Category - age1824	11.6%	10.5%	1.1%	13.0%	-1.4%	12.0%	-0.4%	11.6%	0.0%
Age Category - age2534	17.1%	16.9%	0.2%	15.9%	1.2%	16.5%	0.7%	17.1%	0.0%
Age Category - age3544	19.6%	17.7%	1.9%	17.4%	2.2%	19.7%	0.0%	19.6%	0.0%
Age Category - age4554	20.0%	19.6%	0.4%	20.0%	0.0%	19.6%	0.4%	20.0%	0.0%
Age Category - age5564	14.4%	18.1%	-3.6%	18.2%	-3.8%	15.1%	-0.7%	14.4%	0.0%
Age Category - age6574	9.0%	9.9%	-0.9%	9.3%	-0.3%	8.7%	0.3%	9.0%	0.0%
Age Category - age75up	8.2%	7.3%	0.9%	6.1%	2.1%	8.5%	-0.3%	8.2%	0.0%
Education - LessThanHS	11.9%	9.2%	2.8%	8.4%	3.5%	14.4%	-2.5%	11.9%	0.0%
Education - HSGrad	32.7%	29.3%	3.4%	30.0%	2.7%	31.4%	1.3%	32.7%	0.0%
Education - SomeCol	29.4%	31.7%	-2.3%	32.8%	-3.4%	28.5%	0.9%	29.4%	0.0%
Education - CollegeGrad	17.5%	18.4%	-0.9%	17.7%	-0.2%	16.1%	1.4%	17.5%	0.0%
Education - AdvancedDegree	8.4%	11.5%	-3.0%	11.0%	-2.6%	9.5%	-1.1%	8.4%	0.0%
Census Region - Northeast	18.5%	18.0%	0.5%	18.0%	0.5%	20.0%	-1.5%	18.5%	0.0%
Census Region - Midwest	24.4%	25.9%	-1.5%	27.3%	-2.8%	25.4%	-0.9%	24.4%	0.0%
Census Region - South	37.0%	34.4%	2.6%	33.5%	3.5%	34.6%	2.4%	37.0%	0.0%
Census Region - West	20.1%	21.7%	-1.6%	21.3%	-1.2%	20.0%	0.0%	20.1%	0.0%
Home Ownership Status - NonOwner	23.9%	31.4%	-7.6%	28.6%	-4.7%	30.1%	-6.2%	23.9%	0.0%
Home Ownership Status - Owner	76.1%	68.6%	7.6%	71.4%	4.7%	69.9%	6.2%	76.1%	0.0%
Marital Status - Unmarried	19.5%	25.7%	-6.1%	18.8%	0.7%	21.1%	-1.5%	19.5%	0.0%
Marital Status - Married	57.0%	51.6%	5.4%	59.0%	-2.0%	57.3%	-0.3%	57.0%	0.0%
Marital Status - Never Married	23.5%	22.8%	0.7%	22.2%	1.3%	21.7%	1.8%	23.5%	0.0%
Race/Ethnicity - WhiteNH	79.5%	69.0%	10.5%	69.8%	9.8%	68.5%	11.0%	79.5%	0.0%
Race/Ethnicity - BlackNH	11.9%	15.2%	-3.3%	14.9%	-3.0%	16.0%	-4.1%	11.9%	0.0%
Race/Ethnicity - OtherMultipleNH	2.0%	6.5%	-4.5%	6.7%	-4.7%	6.2%	-4.2%	2.0%	0.0%
Race/Ethnicity - Hispanic	6.6%	9.3%	-2.7%	8.6%	-2.0%	9.3%	-2.7%	6.6%	0.0%
Average Absolute Discrepancy			2.9%		2.5%		2.0%		0.1%

Table B10 - Variables NOT Considered for Raking 2004

		Unweighted		Base Weighted		Old Weight		New Weight	
	Target	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy	Proportion	Discrepancy
R's Children - None	70.7%	76.2%	-5.6%	74.7%	-4.1%	73.6%	-2.9%	75.0%	-4.3%
R's Children - One	12.1%	10.6%	1.4%	11.0%	1.0%	11.1%	1.0%	11.0%	1.1%
R's Children - Two	11.3%	8.2%	3.2%	8.5%	2.8%	8.9%	2.4%	8.3%	3.1%
R's Children - Three	4.4%	3.3%	1.1%	3.6%	0.8%	3.9%	0.5%	3.5%	0.9%
R's Children - Fourormore	1.6%	1.7%	-0.1%	2.1%	-0.6%	2.6%	-1.0%	2.3%	-0.8%
Employment Status - Not Employed	35.6%	33.4%	2.2%	32.5%	3.1%	34.7%	0.9%	33.1%	2.5%
Employment Status - Employed	64.4%	66.6%	-2.2%	67.5%	-3.1%	65.3%	-0.9%	66.9%	-2.5%
Both Parents Born in US	8.8%	16.8%	-8.1%	16.4%	-7.6%	17.3%	-8.5%	14.9%	-6.2%
Parents Not Both Born in US	91.2%	83.2%	8.1%	83.6%	7.6%	82.7%	8.5%	85.1%	6.2%
Turnout Status - Nonvoter	39.3%	21.5%	17.8%	21.1%	18.2%	23.4%	15.9%	21.9%	17.4%
Turnout Status - Voted	60.7%	78.5%	-17.8%	78.9%	-18.2%	76.6%	-15.9%	78.1%	-17.4%
Vote Choice for Congress - Democrat	48.6%	53.1%	-4.4%	52.4%	-3.8%	52.7%	-4.1%	50.5%	-1.9%
Vote Choice for Congress - Republican	51.4%	46.9%	4.4%	47.6%	3.8%	47.3%	4.1%	49.5%	1.9%
Vote Choice for President - Democrat	48.1%	48.5%	-0.3%	48.2%	-0.1%	49.1%	-0.9%	46.8%	1.4%
Vote Choice for President - Republican	50.6%	50.1%	0.5%	50.4%	0.2%	49.3%	1.3%	51.7%	-1.2%
Vote Choice for President - Other	1.3%	1.5%	-0.2%	1.4%	-0.1%	1.6%	-0.4%	1.5%	-0.2%
Average Absolute Discrepancy			4.8%		4.7%		4.3%		4.3%