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Improving Standard Poststratification Techniques For Random-Digit-Dialing Telephone Surveys

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Random-digit-dialing surveys in the United States such as the Behavioral Risk Factor Surveillance System (BRFSS) typically poststratify on age, gender and race/ethnicity using control totals from an appropriate source such as the 2000 Census, the Current Population Survey, or the American Community Survey. Using logistic regression and interaction detection software we identified key "main effect" socio-demographic variables and important two-factor interactions associated with several health risk factor outcomes measured in the BRFSS, one of the largest annual RDD surveys in the United States. A procedure was developed to construct control totals, which were consistent with estimates of age, gender, and race/ethnicity obtained from a commercial source and distributions of other demographic variables from the Current Population Survey. Raking was used to incorporate main effects and two-factor interaction margins into the weighting of the BRFSS survey data. The resulting risk factor estimates were then compared with those based on the current BRFSS weighting methodology and mean squared error estimates were developed. The research demonstrates that by identifying socio-demographic variables associated with key outcome variables and including these variables in the weighting methodology, nonresponse bias can be substantially reduced.
Keywords: nonresponse, weighting, raking, RDD survey, BRFSS

Introduction

Survey researchers are increasingly concerned about potential bias in random-digit dialed (RDD) surveys resulting from frame noncoverage and unit nonresponse. Households with no landline telephones, including those with only cellular (mobile) telephones, are excluded from the RDD sample frame. In the United States 15.8% of households do not have landline telephone service, however, most of these households have one or more working cellular telephones. Currently, 12.8% of households in the U.S. have one or more working cellular telephones (Blumberg and Luke 2007). Unit nonresponse is an issue in any of the various survey modes, but response rates to RDD surveys in the U.S. have been declining steadily (Curtin et al. 2005, Battaglia et al. 2007), in part because of growth in screening technologies, privacy concerns, telemarketing and refusals, and are now typically below 50%.

We attempted to reduce nonresponse bias in a major U.S. health survey by identifying and assessing changes in standard RDD poststratification weighting procedures. After first identifying new potential weighting variables, which were correlates of key outcome measures of interest, we used statistical raking techniques to incorporate these variables into the revised weighting methodology. The research shows that the addition of a few key carefully chosen variables to the weighting methodology can significantly reduce nonresponse bias.

Identifying Factors Related To Unit Nonresponse

Rao et al. (2005) evaluated the degree to which noncoverage of nontelephone households and unit nonresponse contributes to under-representation of important socio-demographic subgroups in RDD surveys. The Behavioral Risk Factor Surveillance System (BRFSS) - an annual RDD survey administered by all the states in the U.S. with assistance from the Centers for Disease Control and Prevention (CDC) to collect health-related information - was used in the analysis. With more than 350,000 interviews conducted annually, the BRFSS is one of the world's largest, ongoing RDD health survey. BRFSS is an important survey that generates state and local prevalence estimates among adults of the major health conditions and behavioral risks associated with premature morbidity and mortality (Mokdad et al. 2003).

Rao et al. evaluated unit nonresponse in six states (California, Illinois, North Carolina, New Jersey, Texas, and Washington). Five of these states had experienced state-level response rates at or below 40% over the past several years,

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Table 1: Thirteen Dichotomous BRFSS Risk Factor Outcome Variables

Health status
Have health care coverage
No leisure time physical activity or exercise past
High blood pressure risk factor
Ever told by doctor you have diabetes
Risk factor for respondents aged 65+ that had a flu shot
Current smoking status risk factor.
Heavy drinking risk
Binge drinking risk factor.
No physical activity or exercise risk factor
Ever been tested for HIV risk factor
Risk factor for overweight or obese
Risk factor for lifetime asthma prevalence

with North Carolina being the exception. They compared the distributions of socio-demographic variables for these six states from the 2003 BRFSS with the distribution of the same variables from the March 2003 Current Population Survey (CPS) for adults living in telephone households. They found that the youngest age group (18-24 years), males, the least educated (Did not graduate from high school), adults who are not currently married, and race/ethnic minority groups (Hispanics and blacks) are under-represented. These findings are consistent with other studies that have identified under-represented groups in RDD telephone surveys conducted in the U.S. (Holbrook et al. 2007).

The identification of socio-demographic factors related to unit nonresponse for use in weighting RDD samples is often based on response propensity modeling (Lee and Valliant 2007). Response propensity modeling is limited to socio-demographic factors that are available for both respondents and nonrespondents, but very little is generally known about the characteristics of nonrespondent households in RDD surveys. We therefore decided to use the alternative approach of identifying socio-demographic factors related to key survey outcome measures.

Table 2: Key Socio-demographic Variables in the BRFSS

Age	1	18 to 24
	2	25 to 34
	3	35 to 44
	4	45 to 54
	5	55 to 64
	6	65 to 74
	7	75 plus
Education	1	Did not graduate High School
	2	Graduated High School
	3	Attended College or Technical School
	4	Graduated from College or Technical School
Employment	1	Unemployed
	2	Not Unemployed
Number of children	1	No children in household
	2	One child in household
	3	Two or more children in household
Household structure	1	HH with only 1 man
	2	HH with only 1 woman
	3	HH with only 1 man and 1 woman
	4	HH with more than 1 man and no women
	5	HH with more men than women
	6	HH with equal men and women
	7	HH with more than 1 woman and no men
	8	HH with more women than men
Gender	1	Male
	2	Female
Race/Ethnicity	1	White only, Non-Hispanic
	2	Black only, Non-Hispanic
	3	Hispanic
	4	All Others
Marital status	1	Married
	2	Never married, member unmarried couple
	3	Divorced, Widowed, Separated

Identifying Factors Related To Key Survey Outcome Variables

Our approach involves identifying socio-demographic factors associated with 13 key risk factor and health condition dichotomous outcome variables in the 2003 BRFSS (see Table 1). This approach focuses on socio-demographic factors related to the key survey dichotomous outcome variables rather than on factors related to unit nonresponse. Smith et al. (2004) discuss the use of predicted probabilities for a dichotomous outcome variable to compensate for unit nonresponse in an RDD survey. This type of model is not limited to socio-demographic factors available for nonrespondents; however, a disadvantage is that it is unknown how well the model fits for the nonrespondent sample and therefore for the entire sample.

The 13 variables were chosen because many are outcome measures used to gauge progress towards the U.S. government's Health People 2010 objectives and all are variables typically found on most health surveillance surveys (U.S. Department of Health and Human Services 2000). To identify demographic covariates to use in the revised weighting methodology we used the same socio-demographic variables examined by Rao et al.: age group, gender, race/ethnicity, marital status, education, employment status, number of children in the household, and number of adults in the household (see Table 2). Using the forward stepwise logistic regression procedure available in SAS Version 8.2, 13 weighted health and risk factor models (one for each outcome variable) were run to determine which socio-demographic variables were the best predictors of the risk factors. We considered predictor variables that entered at the first, second, or third step as the most important predictors. Age entered all 13 models in

Table 3: Key Predictor Variables in the 13 Logistic Regression Models

Variable	Number of Models
Age	13
Education	8
Race/ethnicity	9
Martial Status	4
Gender	3

Table 4: CHAID Results

Interaction	Number of CHAID Models
Age by education	4
Age by gender	3
Gender by race/ethnicity	2
Age by race/ethnicity	2
Education by marital status	2
Marital status by age	2
Marital status by gender	2
Education by race/ethnicity	1

the first, second, or third step. Education and race/ethnicity also entered most of the models (see Table 3).

Furthermore, we identified two-way interactions using weighted Chi-squared Automatic Interaction Detection (CHAID) segmentation trees (Kass 1980). CHAID is an exploratory data analysis method for identifying segments that are predictive of a dichotomous dependent variable. The segments are defined in terms of interactions between the categorical predictor variables.

We first collapsed some of the categories of the above five predictor variables: 1) age was collapsed into three categories (18-34, 35-54, and 55+), 2) education was collapsed into two categories (high school graduate or less, some college or more), and race/ethnicity was collapsed into three categories (non-Hispanic white and other races, non-Hispanic black, and Hispanic). Age by education was a key two-factor interaction in four of the CHAID models. Age by gender was a key two-factor interaction in 3 of the 13 CHAID models (see Table 4).

Adding Variables To The BRFSS Weighting Methodology

The 2003 BRFSS weighting methodology in each state uses poststratification to age-by-gender-by race/ethnicity control totals or to age-by-gender control totals, and is typical of weighting approaches used on many RDD surveys. Poststratification entails cell-by-cell weighting of the sample by ratio-adjusting the design weights of the completed cases in a given cell so that their weight sums to the control total (Kalton 1983). The procedure used for the BRFSS involves calculating a base sampling weight (design weight) followed by poststratification to 14 age-by-gender control totals or 28 age-by-gender-by-race/ethnicity (non-Hispanic white versus all other race/ethnicity groups) totals to obtain the final weight. For states that incorporate race/ethnicity into the poststratification, sample size limitations only allow for the two categories indicated above. However, many states (e.g., California) have significant Hispanic, nonHispanic black, and nonHispanic Asian populations.

The state-level control totals were obtained from Claritas, Inc., a private data company in the U.S. that develops age-by-gender-by-race/ethnicity population estimates for state and sub-state geographic areas. The BRFSS has used Claritas, Inc. for many years as the source for the control totals and it is therefore desirable to continue their use for historical comparison purposes.

Our objective was to adjust the 2003 BRFSS sociodemographic variables for each of the six states to match marginal control totals using raking techniques. Raking involves adjusting the sampling weights of the cases in the sample so that the marginal totals of the adjusted weights on specified characteristics agree with the corresponding totals for the population. This operation is known as raking ratio estimation (Kalton 1983), raking, or sample balancing, and the population totals are usually referred to as control totals. Raking usually proceeds one variable at a time, applying a proportional adjustment to the weights of the cases that belong to the same category of the control variable (Izrael et al. 2000).

In a simple 2-variable example, the marginal totals in various categories for the two variables are known from the entire population, but the joint distribution of the two variables is known only from a sample. In the cross-classification of the sample, arranged in rows and columns, one might begin with the rows, taking each row in turn and multiplying each entry in the row by the ratio of the population total to the weighted sample total for that category, so that the row totals of the adjusted data agree with the population totals for that variable. The weighted column totals of the adjusted data, however, may not yet agree with the population totals for the column variable. Thus the next step, taking each column in turn, multiplies each entry in the column by the ratio of the population total to the current total for that category. Now the weighted column totals of the adjusted data agree with the population totals for that variable, but the new weighted row totals may no longer match the corresponding population totals. The process continues, alternating between the rows and the columns, and agreement on both rows and columns is usually achieved after a small number of iterations.

Bishop et al. (1975) discuss the relationship between iterative proportional fitting and raking. They point out that raking was originally developed not for fitting an unsaturated model to a data set, but rather for combining information from two or more data sets. In the two-way table discussed above, one is in effect fitting a fully saturated loglinear model: the two-factor interaction present in the sample persists after raking, and the one-factor terms (reflected in the population control totals) are also fitted. Thus, in some ways raking can thus be thought of as fitting a ”main effects” model, where the main effects correspond to the given margins.

Development of State-Level Control Totals

Although Claritas, Inc. provides age-by-gender-by-race/ethnicity control totals at the state level; control totals for other socio-demographic sources must be obtained from another source. The Current Population Survey (CPS) was used for this purpose, because it is designed to yield state estimates. The state-level CPS control totals were constructed using the March 2002, 2003, and 2004 CPS. We combined three years of CPS data to reduce the sampling variability of the state-level control totals. This is necessary because the sample size for one year is approximately 110,000 adults and therefore the average state sample size is only around 2,100 adults.

As expected, the Claritas population distribution for age-by-gender or age-by-gender-by-race/ethnicity in a state did not agree exactly with the CPS distribution for 2002-2004, because Claritas uses a population projection technique to estimate the current size of the population in each state. Before obtaining control totals from the CPS, we first took the CPS March supplement person weight for each year and divided it by three. We then ratio-adjusted the CPS weight for the 14 age-by-gender or 28 age-by-gender-by-race/ethnicity categories, so that the CPS-weighted counts agreed with the Claritas counts. This step was necessary because we wanted to compare the impact of adding variables to the BRFSS weighting with the results from using the final BRFSS weight. Once we had a new CPS weight, control totals were produced for race/ethnicity, education, marital status, age by education, and age by race/ethnicity. For each state, we collapsed the race/ethnicity variable to combine small categories that constituted less than 5% of the BRFSS completed interviews in the state with an appropriate race/ethnicity category.

Adjustment for Nontelephone Households

The CPS also has a variable indicating whether the household in which the adult lives has telephone service, so in each state we can estimate the number of adults living in nontelephone households at the time of the CPS interview. The 2003 BRFSS contains a variable indicating whether the respondent lives in a household that has experienced an interruption in telephone service of a week or longer. Using the BRFSS design weight, we estimated the percentage of adults in a state living in telephone households with an interruption in telephone service. Following the procedure detailed below, we then created a CPS control total margin for: 1) adults in telephone households without an interruption in telephone service, and 2) adults in telephone households with an interruption in telephone service and adults living in nontelephone households.

Empirical evidence suggests that telephone households with interruptions in telephone service are often more similar to nontelephone households than are either telephone households without interruptions or all telephone households (Keeter 1995; Frankel et al. 1999). Frankel et al. (2003) used the National Health Interview Survey, which covers telephone and nontelephone households and includes a question on whether the household was without telephone service in the past year, to show that households with an interruption in telephone service are similar to nontelephone households.

To take advantage of this relationship, an RDD survey can collect information on whether each selected household experienced an interruption in telephone service of one or week or longer in the past 12 months. Then as described below the weights of households with interruptions in telephone service can be separately adjusted to compensate for the noncoverage of nontelephone households. The inclusion of the nontelephone margin in the raking is intended to compensate for noncoverage from the exclusion of adults living in nontelephone households.

For a given state let N denote the total number of adults living in households (i.e., both telephone and nontelephone households) from the CPS. Also from the CPS, let N_t denote the total number of adults in telephone households and N_{nt} the total number of adults in nontelephone households. Then $N = N_t + N_{nt}$. Let r denote the estimated proportion of adults living in telephone households in the survey having interruptions in telephone service. We estimate the total number of adults living in households in the population having interruptions in telephone service as $\hat{N}_{tI} = rN_t$. Through raking we seek to adjust the weights of adults in households with interruptions in telephone service to sum to the total $N_{nt} + \hat{N}_{tI}$. Also, we seek to adjust the weights of adults living in households without interruptions in telephone service to sum to the total $N_t - \hat{N}_{tI}$.

Raked Weights

For each of the 13 risk factor outcome variables, we used the BRFSS design weight and the BRFSS final weight to estimate the percent of adults with a risk factor or health condition in each of the six states. We then used a SAS raking macro (Battaglia et al. 2004) to create 10 potential new weights for the BRFSS in each of the six states. The details of the margins included in each raking are shown in Table 5. The logic to the ordering of the 10 rakings is as follows: 1) the first 5 rakings do not include the two-category nontelephone adjustment margin described above, 2) most survey statisticians would give highest priority to including a detailed race/ethnicity margin, even if a state has an age-by-gender-by-race/ethnicity margin limited to non-Hispanic white versus all other race/ethnic groups, 3) based on the logistic regression modeling results, education will next be entered as a margin, followed by marital status, and 4) based on the CHAID results, the age-by-education two-variable margin will next be entered and finally the age-by-race/ethnicity two-variable margin will be entered into the raking.

Results For The Six States

As discussed earlier the BRFSS uses poststratification based on age-by-gender-by race/ethnicity or age-by-gender. For comparative purposes, we show the results of the 10 rakings for two typical states - California and Texas. California

Table 5: Margins Included in the 10 BRFSS Rakings

Without interruption in telephone service margin:	
1. Age by gender or age by gender by race/ethnicity	And race/ethnicity
2. Age by gender or age by gender by race/ethnicity and race/ethnicity	And education
3. Age by gender or age by gender by race/ethnicity, race/ethnicity, education	And marital status
4. Age by gender or age by gender by race/ethnicity, race/ethnicity and marital status	And age by education
5. Age by gender or age by gender by race/ethnicity, race/ethnicity and age by education	And age by race/ethnicity
With interruption in telephone service margin:	
6. Age by gender or age by gender by race/ethnicity	And race/ethnicity and interruption in telephone service
7. Age by gender or age by gender by race/ethnicity and race/ethnicity	And education and interruption in telephone service
8. Age by gender or age by gender by race/ethnicity, race/ethnicity, education	And marital status and interruption in telephone service
9. Age by gender or age by gender by race/ethnicity, race/ethnicity and marital status	And age by education and interruption in telephone service
10. Age by gender or age by gender by race/ethnicity, race/ethnicity and age by education	And age by race/ethnicity and interruption in telephone service

uses age-by-gender-by-race/ethnicity poststratification, and only 2.8% of its adults reside in nontelephone households according to the CPS. The Texas BRFSS used age-by-gender poststratification and a higher proportion of its adults (5.7%) reside in nontelephone households based on the CPS. The race/ethnicity margin that we created using the 5% rule for Texas contains three categories: non-Hispanic white, non-Hispanic black, and Hispanic plus non-Hispanic other races. For California, the race/ethnicity margin contains four categories - non-Hispanic white, non-Hispanic black, Hispanic, and non-Hispanic other races. We show results only for the questions about general health status and health insurance coverage (see Figures 1 to 4), but the findings for the other risk factor variables are similar.

In California, the addition of the race/ethnicity margin has a fairly small effect on the general health risk factor and health insurance coverage estimates. The raking that includes race/ethnicity and adds education increases the risk factor estimates by a considerable amount. The addition of marital status, age by education, and age by race/ethnicity causes little further change in the estimates. The inclusion of the nontelephone margin in the raking has almost no impact on the general health status estimates but raises the risk factor estimates for health insurance coverage. Compared to the risk factor estimates based on the final weight, the risk factor estimates from raking #10, which includes the nontelephone margin and the age-by-race margin, increase by 9.9% and 6.2%, respectively.

In Texas, the addition of the race/ethnicity margin has a larger effect on the general health status and health insurance coverage risk factor estimates. The raking that includes race/ethnicity and adds education further raises the estimates. The addition of marital status, age by education, and age by race/ethnicity causes a small additional change in the estimate. The inclusion of the nontelephone margin in the raking noticeably raises the risk factor estimates. Compared to the risk factor estimate based on the final weight, the risk factor estimates from raking #10, which includes the nontelephone margin and the age-by-race margin, increase by 14.9% and 10.9%, respectively.

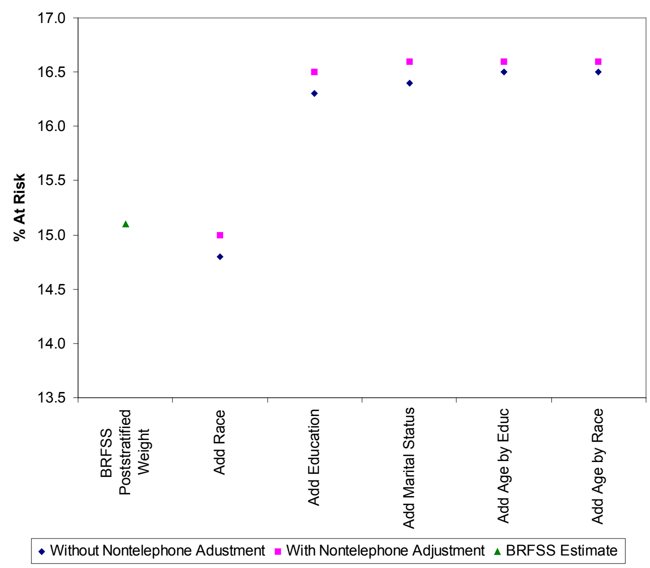

Figure 1. Graph of California General Health Status Risk Factor Estimates for BRFSS Poststratified Weight and 10 Raking Weights

Estimates of Mean Squared Error

We next developed eleven estimates of the mean squared error (MSE) of the risk factor estimates (based on the de-

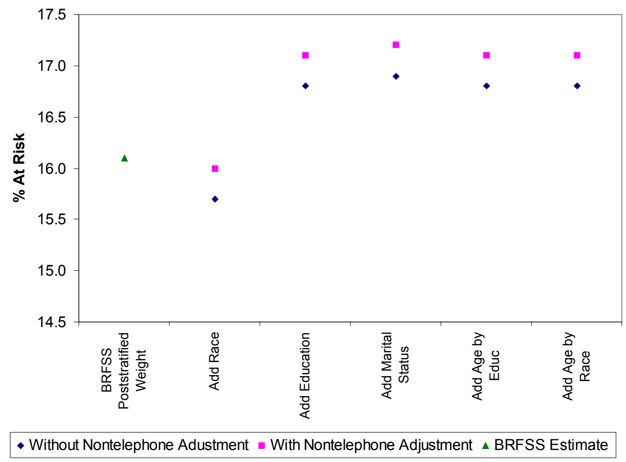

Figure 2. Graph of California Health Insurance Coverage Risk Factor Estimates for BRFSS Poststratified Weight and 10 Raking Weights

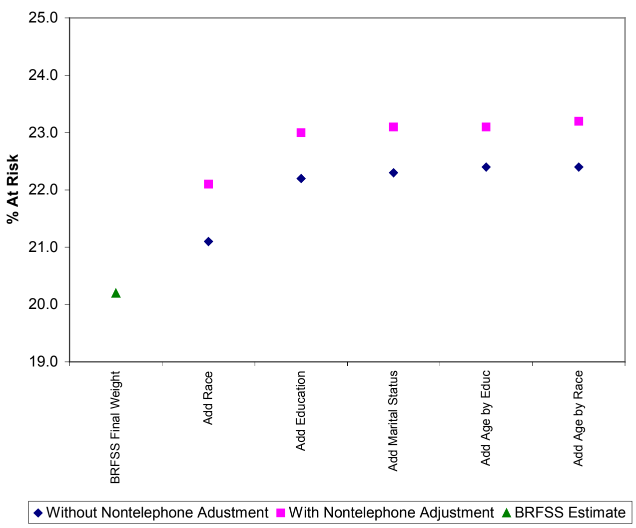

Figure 3. Graph of Texas General Health Status Risk Factor Estimates for BRFSS Poststratified Weight and 10 Raking Weights

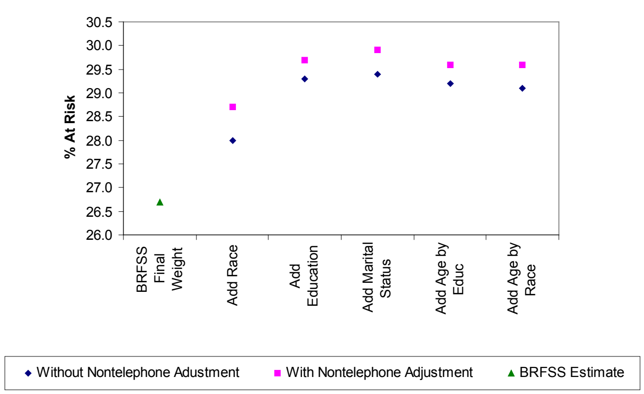

Figure 4. Graph of Texas Health Insurance Coverage Risk Factor Estimates for BRFSS Poststratified Weight and 10 Raking Weights

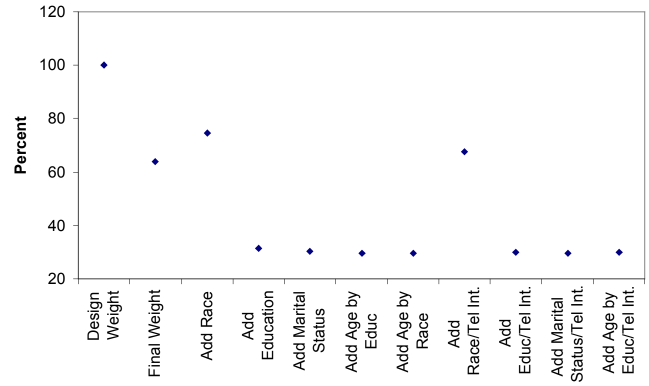

Figure 5. Graph of Indexed Relative Mean Squared Error for California General Health Status Risk Factor Estimates

sign weight, the final weight, and raking weights #1 to #9 = 11 estimates) by treating the estimates from raking #10 as unbiased, because they incorporate all of the key sociodemographic variables. The true risk factors in the population are unknown and this approach assumes that risk factor estimates resulting from the full adjustment are closest to the true values.

The bias component of an estimated MSE equals the squared difference of the risk factor estimate from raking #10 and one of the eleven risk factor estimates. The variance component of the estimated MSE equals the squared standard error, calculated using SUDAAN (Research Triangle Institute 2001), of that same risk factor estimate. Eleven relative MSE estimates were calculated by dividing the square root of the MSE by the risk factor estimate from raking #10. Finally, we indexed the relative MSE estimates to the relative MSE estimates resulting from the BRFSS design weight (the estimate assumed to have the largest bias).

The indexed relative MSE results for the general health risk factor and health insurance coverage estimates for California and Texas are shown in Figures 5 to 8. By definition, the indexed relative MSE for the design weight estimates is 100%. Because the inclusion of more variables in the raking typically increases the variance, it is possible for the indexed relative MSE for estimates based on one of the other weights to exceed 100%. The ideal result in terms of bias reduction is for the indexed relative MSE to be well below 100%.

For California, the estimates based on the final weight and those for raking #1 (includes race/ethnicity) yield a reduction in the indexed relative MSE. However, a large additional reduction is seen with the addition of education to the raking. The inclusion of the nontelephone adjustment margin in the raking has very little impact on the indexed relative MSE in California. We see a similar pattern in Texas except that the raking that includes race/ethnicity substantially lowers the indexed relative MSE. Similar to California, we also see that the addition of education to the raking causes a further large decline in the indexed relative MSE. However, unlike California, the inclusion of the nontelephone adjustment margin has a noticeable impact on further reducing the

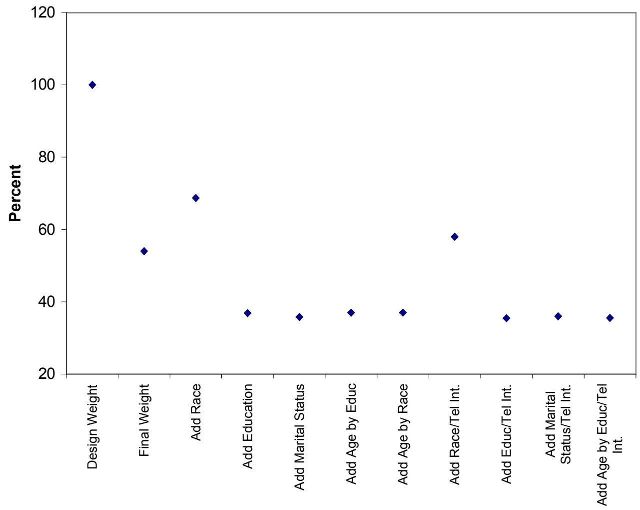

Figure 6. Graph of Indexed Relative Mean Squared Error for California Health Insurance Coverage Risk Factor Estimates

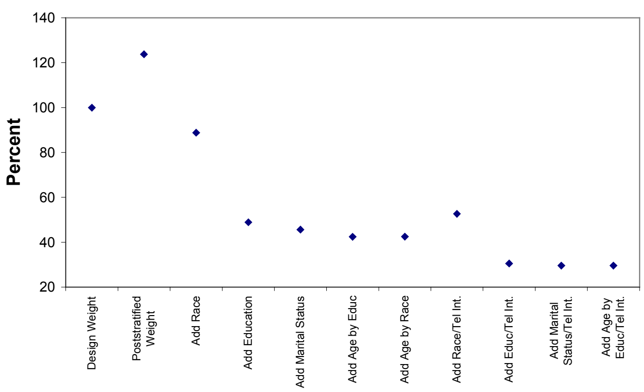

Figure 7. Graph of Indexed Relative Mean Squared Error for Texas General Health Status Risk Factor Estimates

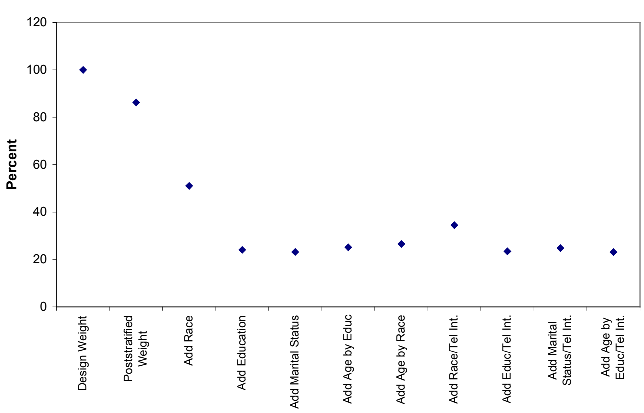

Figure 8. Graph of Indexed Relative Mean Squared Error for Texas Health Insurance Coverage Risk Factor Estimates

indexed relative MSE for general health status. The inclusion of education, a socioeconomic status variable, is clearly important; however, the inclusion of the nontelephone adjustment margin in the raking can also be important for bias reduction. For all four risk factor estimates the indexed relative MSE declines to below 40% indicating a potential for substantial bias reduction.

Applying the Raking Method To All States in the U.S.

Based on what we learned in the six states, a new weight was developed for each of the 50 states and the District of Columbia. Following the approach of using the 2002-2004 March CPS, the CPS weight for the adults in each state was ratio-adjusted to the Claritas age-by-gender or age-by-gender-by-race/ethnicity distribution. Raking margins were then developed for race/ethnicity, education, marital status, age by gender, age by education, age by race/ethnicity, and for the nontelephone adjustment. The inclusion of the nontelephone adjustment margin is important, because the states vary considerably, as illustrated by California and Texas, with respect to the percent of adults living in nontelephone households, which are excluded from RDD surveys. For the race/ethnicity margin, a category-collapsing procedure was used to ensure that each category had at least 5.0% of the completed BRFSS interviews. For the age-by-race/ethnicity margin, the race/ethnicity categories developed for the one-variable race/ethnicity margin were used and age categories were collapsed to ensure that each contained at least 5.0% of the completed BRFSS interviews.

The health and risk factor estimates based on the raking weight were then compared with the estimates based on the BRFSS poststratified weight. In Figures 9 and 10, the BRFSS general health status risk factor and health insurance coverage estimates for the 50 states and DC are given on the horizontal axis. The vertical axis shows the percentage difference. All of the percentage differences are at least zero, indicating that the raking leads to risk factor estimates that are higher than the usual BRFSS estimates, generally by one-half to three percentage points. Similar results were found for the other risk factor estimates. To better assess the magnitude of the differences we divided the percentage difference by the standard error of the estimate based on the BRFSS final weight. This expresses the difference in standard error units. One-dimensional jittered dot plots are shown in figures 11 and 12. Looking at the percentage differences in standard error units, most fall between one and five percentage points indicating that the observed differences are fairly large relative to the standard errors of the estimates.

Conclusions

Data based on self-reports from a telephone survey can lead to an under-estimation of some risk factors in the population. For many states response rates have fallen below 50%, increasing the potential for nonresponse bias. People with no telephone service tend to be of lower socio-economic status, a characteristic associated with increased risk factors.

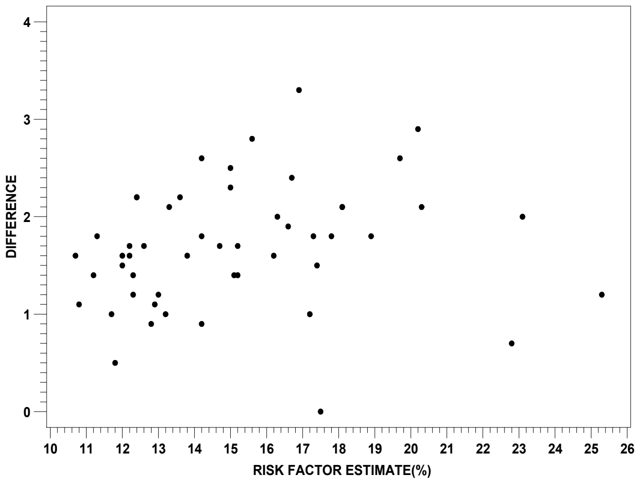

Figure 9. Percentage Difference in General Health Status Risk Factor Estimates (Raking Poststratification) Plotted Against BRFSS General Health Risk Factor Estimate for 50 States and District of Columbia

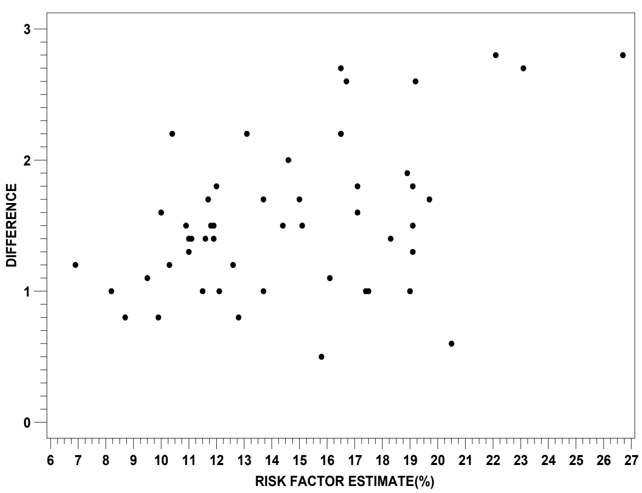

Figure 10. Percentage Difference in Health Insurance Coverage Risk Factor Estimates (Raking Poststratification) Plotted Against BRFSS General Health Risk Factor Estimate for 50 States and District of Columbia

Moreover, as the use of cellular telephones increases, another layer of complexity is added in producing valid survey estimates. The methodology presented here improves upon standard poststratification approaches used in RDD surveys (which tend to rely on sex, age, and race/ethnicity), ensuring a better weighting mechanism to overcome these limitations.

By identifying socio-demographic variables associated with key risk factor variables and including these variables in the weighting methodology, we were able to substantially reduce nonresponse bias in the state risk factor estimates. The inclusion of a nontelephone adjustment margin can also lead to noncoverage bias reduction in some states.

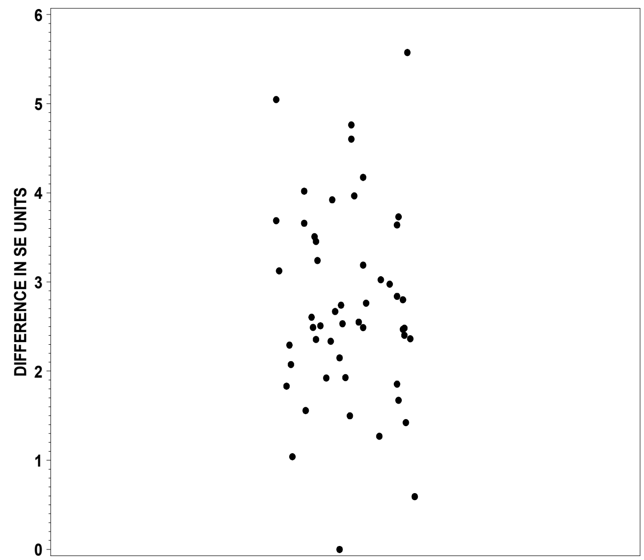

Figure 11. Percentage Difference in General Health Status Risk Factor Estimates (Raking Poststratification) in Standard Error (SE) Units for 50 States and District of Columbia

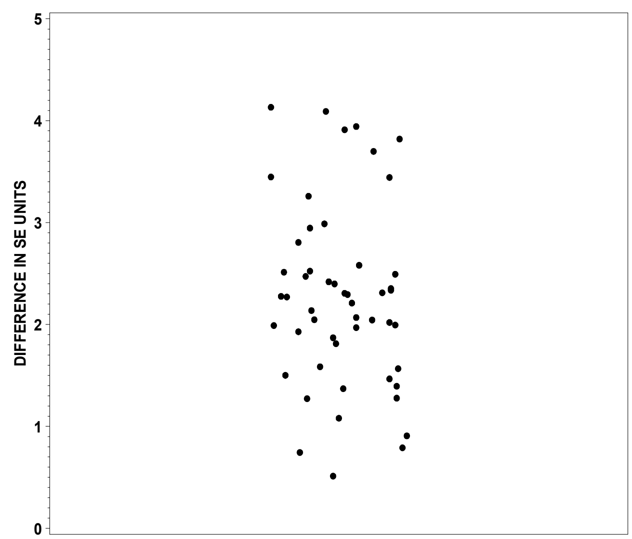

Figure 12. Percentage Difference in Health Insurance Coverage Risk Factor Estimates (Raking Poststratification) in Standard Error (SE) Units for 50 States and District of Columbia

We found that many of the health and risk factor estimates increased noticeably when these variables were incorporated into the weighting using raking. Indeed, weighting through simple poststratification by age-sex or age-sex-race may be obsolete, and there is a need to further expand the list of variables to be accounted for in weighting. The inclusion of education in the weighting of RDD surveys is particularly important. The methodology outlined here will better ensure that telephone survey results more closely match those produced by higher response rate area probability surveys conducted in homes.

References

Battaglia, M. P., Hoaglin, D. I. D. C., & Frankel, M. R. (2004). *Tips and tricks for raking survey data.* 2004 Proceedings of the Annual Meeting of the American Statistical Association (CD-ROM), Alexandria. (VA: American Statistical Association)

Battaglia, M. P., Khare, M., Frankel, M. R., Murray, M. C., Buckley, P., & Peritz, S. (2007). Response rates: How have they changed and where are they headed? In J. M. Lepkowski et al. (Eds.), *Advances in telephone survey methodology.* New York: John Wiley & Sons.

Bishop, Y. M. M., Fienberg, S. E., & Holland, P. W. (1975). *Discrete multivariate analysis: Theory and practice.* MA: MIT Press. (Cambridge)

Blumberg, S. J., & Luke, S. V. (2007, May 14). *Wireless substitution: Early release estimates based on data from the national health interview survey, july-december 2006.* National Center for Health Statistics. Available from `www.cdc.gov/nchs/nhis.htm`

Curtin, R., Presser, S., & Singer, E. (2005). Changes in telephone survey nonresponse over the past quarter century. *Public Opinion Quarterly*, *69*, 87-98.

Frankel, M. R., Srinath, K. P., Battaglia, M. P., Hoaglin, D. C., Wright, R. A., & Smith, P. J. (1999). *Reducing nontelephone bias in rdd surveys.* Proceedings of the Section on Survey Research Methods, Alexandria, pp. 934-939. (VA: American Statistical Association)

Frankel, M. R., Srinath, K. P., Hoaglin, D. C., Battaglia, M. P., Smith, P. J., Wright, R. A., et al. (2003). Adjustments for non-telephone bias in random-digit-dialling surveys. *Statistics in Medicine*, *22*, 1611-1626.

Holbrook, A. L., Krosnick, J. A., & Pfent, A. (2007). The causes and consequences of response rates in surveys by the new media and government contractor survey research firms. In J. M. Lepkowski et al. (Eds.), *Advances in telephone survey methodology.* New York: John Wiley & Sons.

Izrael, D., Hoaglin, D. C., & Battaglia, M. P. (2000). *A sas macro for balancing a weighted sample.* Proceedings of the Twenty-Fifth Annual SAS Users Group International Conference, Cary, pp. 1350-1355. (NC: SAS Institute Inc)

Kalton, G. (1983). *Compensating for missing survey data.* Institute for Social Research. (The University of Michigan, Ann Arbor, MI)

Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. *Journal of Applied Statistics*, *29*, 119-127.

Keeter, S. (1995). Estimating telephone noncoverage bias with a telephone survey. *Public Opinion Quarterly*, *59*, 196-217.

Lee, S., & Valliant, R. (2007). Weighting telephone samples using propensity scores. In J. M. Lepkowski et al. (Eds.), *Advances in telephone survey methodology.* New York: John Wiley & Sons.

Mokdad, A. H., Stroup, D., & Giles, H. W. (2003). Public health surveillance for behavioral risk factors in a changing environment: Recommendations from the behavioral risk factor surveillance team. *MMWR*, *52*(No. RR-9), 1-12.

Rao, S. R., Link, M. W., Battaglia, M. P., Frankel, M. R., Giambo, P., & Mokdad, A. H. (2005). *Assessing representativeness in rdd surveys: Coverage and nonresponse in the behavioral risk factor surveillance system.* Proceedings of the Annual Meeting of the American Statistical Association (CD-ROM), Alexandria. (VA: American Statistical Association)

Research Triangle Institute. (2001). *Sudaan users' guide manual, release 8.0. research triangle park.* (NC: Research Triangle Institute)

Smith, P. J., Hoaglin, D. C., Rao, J. N. K., Battaglia, M. P., & Daniels, D. (2004). Evaluation of adjustments for partial nonresponse bias in the u.s. national immunization survey. *Journal of the Royal Statistical Society, Series A*, *167*, 141-156.

U.S. Department of Health and Human Services. (2000). *Tracking healthy people 2010.* Washington, DC: U.S. Government Printing Office.