Paper 133-2007

Alternatives for Analysis of Complex Sample Surveys: A Comparison of SAS®, SUDAAN®, and AM® Software

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ABSTRACT

Data collected from complex sample surveys are frequently used in secondary data analysis. The analysis of such data using standard statistical software yields biased point estimates of parameters and incorrect standard errors as a result of unequal probabilities of selection of observations, stratification and clustering, and unit nonresponse. The appropriate analysis of data from complex sample surveys requires the use of software that incorporates sample weights and accurate estimates of variance. SAS procedures such as PROC SURVEYMEANS and PROC SURVEYLOGISTIC provide one approach to such analyses, as does the use of specialized stand-alone software (such as AM) or packages that integrate with SAS (such as SUDAAN SAS-Callable). This paper provides an introduction to the special statistical requirements for the analysis of complex survey data and a comparison of statistical results when data are analyzed using SAS v9.1.3, SUDAAN SAS9-Callable 9.0.1, and AM v.0.06. The paper includes samples of code and illustrations of output from each software package.

INTRODUCTION

With the increase in the availability of nationally representative data across a variety of disciplines, secondary data analysis of large, complex sample surveys has become more common among social and behavioral scientists over the last 20 years. Given the many benefits of conducting secondary data analysis of nationally representative data, it is not surprising that the use of complex sample survey data has become common place among social and behavioral science researchers. For example, conducting secondary data analysis of large, secondary data sources is usually more cost effective than collecting primary data and secondary data sources are typically easier to obtain than primary data (Hofferth, 2005; Rosenberg, Greenfield, & Dimick, 2006). Other benefits of conducting secondary data analysis of large, complex surveys include large sample size, increased power and generalizability due to the population representativeness, and the large number of variables (Hofferth, 2005; McCall & Applebaum, 1991; Rosenberg, Greenfield, & Dimick, 2006). Also, many secondary data sources are longitudinal in nature, thus they allow researchers to investigate different questions than could be addressed with primary, cross-sectional data.

However, just as there are benefits to conducting secondary data analysis on large, complex sample survey data, there are also drawbacks associated with this type of research. One of the most commonly noted limitations and concerns of secondary data analysis of complex sample surveys is the fact that the data were collected for purposes other than the purpose of the secondary analysis (McCall & Applebaum, 1991). The time and costs associated with learning about the secondary data source including survey items, data structure, and technical documentation are two other limitations of conducting secondary data analysis on large, complex sample surveys (Hofferth, 2005; McCall & Applebaum, 1991). Another limitation relates to data quality, including missing data, how latent constructs are operationalized, and the quality of supporting documentation for the data source (McCall & Applebaum, 1991; Rosenberg, Greenfield, & Dimick, 2006). Lastly, contrary to primary research, in secondary data analysis the data often dictate the research question which is opposite of the traditional methods most researchers learned as graduate students (Hofferth, 2005; McCall & Applebaum, 1991).

SOURCES OF COMPLEX SAMPLE SURVEY DATA

The first step in conducting secondary data analysis on large, complex sample survey data is locating a data source. Whereas there are many social science databases available through a variety of archives, three common sources include the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan, National Center for Education Statistics (NCES), and National Center for Health Statistics (NCHS). The ICPSR is the world's largest repository and dissemination service of social science data (Kiecolt & Nathan, 1985). Within the ICPSR, data sources are stored in one of 15 archives, arranged by topic area. Example archives available from the ICPSR include Census 2000, Substance

Abuse and Mental Health, and International Archive of Education Data (ICPSR, n.d.). NCES and NCHS also provide numerous complex sample survey data sources available to researchers. However, unlike the ICPSR, the NCES and NCHS are more discipline specific. For example, NCES only offers education-related data sources [e.g., High School and Beyond, National Household Education Survey, Schools and Staffing Survey (NCES, n.d.)] and NCHS only provides health-related data sources [e.g., National Health Interview Survey, National Survey of Children's Health, National Survey of Family Growth, (Centers for Disease Control and Prevention, 2004)].

BACKGROUND ON COMPLEX SAMPLE SURVEYS

From the perspective of statistical analysis, data from complex sample surveys differ from those obtained via simple random sampling in four respects. First, the probabilities of selection of the observations are not equal. Oversampling of certain subgroups in the population is frequently employed in survey sample design to allow reasonable precision in the estimation of parameters. In addition, multi-stage sampling results in clustered observations in which the variance among units within each cluster is less than the variance among units in general (i.e., intraclass correlation). Further, stratification in sampling (e.g., geographical stratification) insures appropriate sample representation on the stratification variable(s), but yields negatively biased estimates of the population variance. Finally, unit nonresponse and other post-stratification adjustments are usually applied to the sample to allow unbiased estimates of population characteristics (Brick & Kalton, 1996).

Sample Weights. Typically, observations from complex sample surveys are weighted such that an observation's weight is equal to the reciprocal of the probability of selection. That is, observations more likely to be selected (e.g., from oversampling) receive a smaller weight than observations less likely to be selected. In data available from large scale surveys, weights are provided such that the sum of the weights equals either the sample size (relative weights)

$$\sum_{i=1}^{n} w_i = n$$

or the population size (raw weights)

$$\sum_{i=1}^{n} w_i = N$$

The weights are applied in the computation of statistics from the sample observation. For example, the sample mean is computed as

$$\bar{X} = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i}$$

Estimation of Variances. The estimation of sampling error is a critical component of survey analysis. Sampling error provides an index of the precision of point estimates (e.g., sample means or proportions) and is used for the calculation of both confidence intervals and hypothesis tests. For complex sample surveys (involving stratification, multi-stage sampling, and unequal probabilities of selection) the calculation of sampling error differs from the calculation used in simple random sampling. Unfortunately, software designed for general data analysis, including common SAS procedures such as PROC GLM or PROC LOGISTIC, calculate standard errors under the assumption of simple random sampling. A variety of methods are available for appropriate estimation of sampling error, including Taylor linearization, replication methods (Balanced Repeated Replications, Jackknife, and Bootstrap) and the use of design effects (DEFF and DEFT).

The Taylor series linearization is used in many statistical applications to obtain approximate values of functions that are difficult to calculate precisely. Because most statistical estimates from complex sample surveys are not simple linear functions of the observations, a Taylor series expansion may be used to obtain an approximation of the estimate based on the linear (first-order) part of the Taylor series. The variance of this approximation may then be used to estimate the variance of the original statistic of interest. The Taylor series approach tends to be computationally fast (in comparison with replication methods) but carries the limitation that a separate formula must be developed for each estimate of interest.

In contrast to the Taylor series linearization approach, replication methods rely on the power of computers rather than the mathematics of statistics. These approaches to variance estimation take repeated subsamples from the observed data, calculate the desired statistic in each subsample, and estimate the variance of the statistic by computing the variability of the subsample values. The different methods that are subsumed under the replication umbrella simply represent different approaches to forming these subsamples. The most popular methods of replication are Balanced Repeated Replication (BRR), the jackknife, and the bootstrap. The BRR approach divides each sampling stratum into two primary sampling units and creates subsamples by randomly selecting one of the units from each stratum to represent the entire stratum. In contrast, the jackknife method removes one stratum at a time to create each replicate. Finally, the bootstrap approach generates replicates by randomly sampling with replacement from the obtained sample responses. Each bootstrap replicate is drawn using the same sample size and the same sample structure (number of observations sampled with replacement from each stratum) as the total sample.

In contrast to the linearization and replication approaches, many surveys provide estimates of design effects (DEFFs) that may be used to adjust the sampling error calculated by techniques that assume simple random sampling (e.g., the estimates used by usual SAS procedures such as PROC GLM or PROC LOGISTIC). The DEFF is simply the ratio of the variance obtained under the sampling method used to the variance that would be obtained in simple random sampling:

$$DEFF = \frac{\sigma_C^2}{\sigma_S^2}$$

The value of the DEFF differs across variables measured in sample surveys and estimates of DEFF are typically provided for the major variables of interest. The obtained standard error of a statistic, computed assuming simple random sampling, is multiplied by the square root of the DEFF (often called the design factor, DEFT) to obtain an improved estimate of the actual standard error.

SOFTWARE OPTIONS FOR COMPLEX SURVEY ANALYSIS

When conducting secondary data analysis using complex survey data, researchers have several statistical software options designed to handle the design effects by allowing the use of sample weights and applying appropriate sampling error estimation techniques. In the social and behavioral sciences, SAS SURVEY procedures, SUDAAN SAS-Callable, and AM are three of the commonly used software packages for analysis of complex sample survey data. The following sections provide a brief description of the available statistics and the methods for variance estimation for each of the three software programs.

SAS v9.1.3. SAS users can take into account the complex sampling design of large scale surveys by using the survey procedures available in SAS/STAT version 7 and higher. All four survey procedures (SURVEYMEANS, SURVEYFREQ, SURVEYREG, and SURVEYLOGISTIC) use Taylor linearization to estimate sampling errors (SAS Institute Inc., 2004). Also, when working with large scale data sets that include replicate weights, SAS users can use a macro to calculate properly weighted variance estimates for summary statistics (mean and median) and corresponding standard errors using JK2 estimates (Gossett, Simpson, Parker, & Simon, 2002).

SAS procedures require the familiar syntax (DATA = to specify data sets; VAR, TABLE, and MODEL statements; as well as WEIGHT, STRATUM, and CLUSTER statements). An example of SAS syntax for PROC SURVEYREG and partial output from the procedure is provided in Figure 1.

SUDAAN SAS9-Callable 9.0.1. Developed with advice and assistance from the SAS Institute, the current SUDAAN software package actually evolved from a single general survey analysis procedure in SAS (STDERR, Research Triangle Institute, 2004). SUDAAN was specifically created in response to the need for statistical software that could appropriately calculate variance estimations for data from complex sample surveys. Today, the SUDAAN software package includes a variety of analytic procedures and variance estimation methods. For example, SUDAAN offers both Taylor-series linearization and replication methods (BRR and Jackknife) for variance estimation of descriptive statistics and regression parameters (Research Triangle Institute, 2004). Specific analytic procedures available in SUDAAN 9.0.1 include: CROSSTAB, RATIO, DESCRIPT, REGRESS, LOGISTIC, MULTILOG, LOGLINK, SURVIVAL, and KAPMEIER (Research Triangle Institute, 2004).

The SUDAAN procedures require syntax similar to SAS (e.g., DATA =, VAR, TABLE, MODEL, and WEIGHT). An example of SUDAAN syntax for PROC REGRESS and partial output from the procedure is provided in Figure 2.

```
proc surveyreg data=one;
      stratum SSTRATID;
      weight byqwt;
      model by2xmstd = bys12 black hispanic api indian bys79a bycncpt1 byses
      / adjrsq anova clparm deff;
      run;
```

```
                    Estimated Regression Coefficients


                           Standard                           95% Confidence
Parameter      Estimate       Error    t Value   Pr > |t|         Interval


Intercept    49.8468344    0.23865413    208.87     <.0001    49.3790544 50.3146144
BYS12        -0.2552849    0.13557242     -1.88     0.0597    -0.5210170  0.0104472
black        -5.3744166    0.19162169    -28.05     <.0001    -5.7500094 -4.9988237
hispanic     -2.9007618    0.20588290    -14.09     <.0001    -3.3043078 -2.4972159
api           1.5363492    0.34306029      4.48     <.0001     0.8639253  2.2087731
indian       -3.3691119    0.30753087    -10.96     <.0001    -3.9718955 -2.7663284
BYS79A        1.3091386    0.04918166     26.62     <.0001     1.2127388  1.4055383
BYCNCPT1      0.8050397    0.09260497      8.69     <.0001     0.6235270  0.9865523
BYSES         4.6295890    0.09049605     51.16     <.0001     4.4522100  4.8069681
```

Figure 1. SAS v9.13 OLS Regression Code and Partial Output with Complex Sample Survey Data.

```
PROC REGRESS DATA = one FILETYPE = SAS DESIGN = WR;
      nest SSTRATID;
      weight byqwt;
      MODEL by2xmstd = bys12 black hispanic api indian bys79a bycncpt1 byses;
      run;
```

```
Variance Estimation Method: Taylor Series (WR)
SE Method: Robust (Binder, 1983)
Working Correlations: Independent
Link Function: Identity
Response variable BY2XMSTD: MATHEMATICS STANDARDIZED SCORE
by: Independent Variables and Effects.
------------------------------------------------------------------------
Independent
  Variables and      Beta                   Lower 95%    Upper 95%
  Effects            Coeff.       SE Beta   Limit Beta   Limit Beta
------------------------------------------------------------------------
Intercept              49.85         0.24        49.38        50.31
SEX OF RESPONDENT      -0.26         0.14        -0.52         0.01
BLACK                  -5.37         0.19        -5.75        -5.00
HISPANIC               -2.90         0.21        -3.30        -2.50
API                     1.54         0.34         0.86         2.21
INDIAN                 -3.37         0.31        -3.97        -2.77
TIME SPENT ON MATH
  HOMEWORK EACH WEEK    1.31         0.05         1.21         1.41
SELF CONCEPT 1          0.81         0.09         0.62         0.99
SOCIO-ECONOMIC
  STATUS COMPOSITE      4.63         0.09         4.45         4.81
------------------------------------------------------------------------
```

Figure 2. SUDAAN SAS9-Callable 9.0.1 OLS Regression Code and Partial Output with Complex Sample Survey Data.

AM *v.0.06.* Originally developed as a specialized software program for analyzing large-scale assessment data, AM has evolved into a more generalized and growing tool for analyzing data from complex samples (American Institutes for Research, n.d.a). AM is still in a Beta release version and includes the following procedures for analysis of complex survey data: descriptive statistics, frequencies, percentiles, correlation, OLS regression, probit and logit, generalized multinomial logit, and generalized Mantel Haenszel chi-square (American Institutes for Research, n.d.b). By default, all procedures in the software automatically use a Taylor-series approximation to estimate standard errors. However, use of a jackknife or other replication technique is available for a handful of procedures.

Unlike SAS and SUDAAN, the AM software does not require syntax. Instead, in an effort to make the software user-friendly for field researchers, the interface is click-and-drag. Figure 3 provides a sample screen shot of the regression input in AM, and Figure 4 provides a sample of the html output from this procedure.
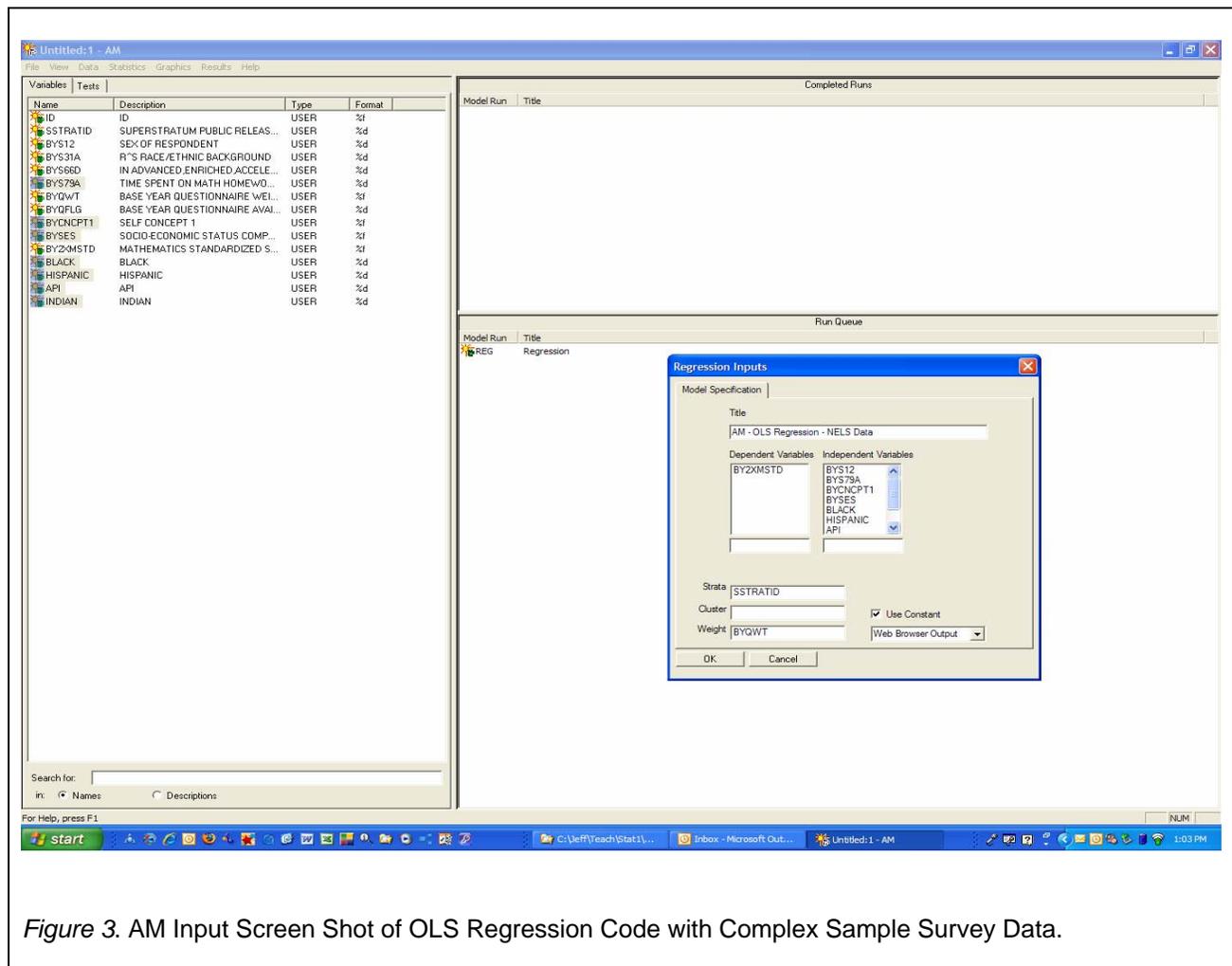

Figure 3. AM Input Screen Shot of OLS Regression Code with Complex Sample Survey Data.
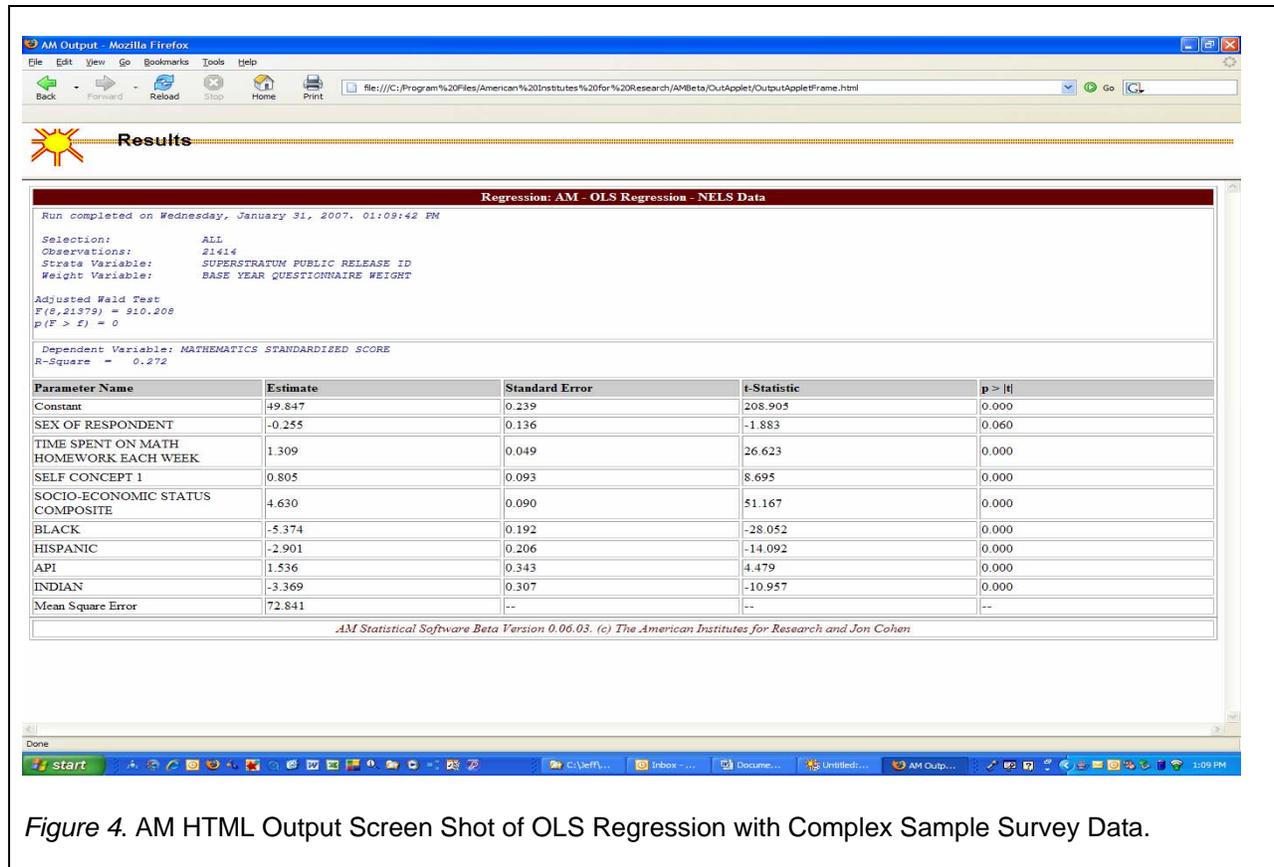
5

Figure 4. AM HTML Output Screen Shot of OLS Regression with Complex Sample Survey Data.

COMPARISON OF STATISTICAL RESULTS

Data from the National Education Longitudinal Study of 1988 (NELS88, NCES, n.d.) were used to compare point estimates and standard errors obtained from SAS, SUDAAN, and AM for four commonly used analytic techniques - frequencies, means, OLS regression, and logistic regression. The comparison included five procedures for each of the statistical techniques. More specifically, for each statistical technique (i.e., frequencies, means, OLS regression, and logistic regression), three SAS procedures were performed (regular procedure without sample weights, regular procedure with sample weights, and the relevant SURVEY procedure), one SUDAAN procedure was performed, and one AM procedure was performed. Both the OLS and logistic regression models contained the same set of regressors - five dichotomous variables and three continuous variables.

Results from the analysis of frequencies are presented in Table 1. The unweighted results from SAS PROC FREQ produce different percentages than those of all four weighted procedures, whereas the weighted procedures provide identical percentages (except for a different rounding level for the AM program). The standard errors of the percentages provided by SAS PROC SURVEYFREQ, SUDAAN PROC CROSSTAB, and AM are identical and the 95% confidence intervals provided by the two former programs are identical.

Table 1
Comparison of Results from SAS, SUDAAN, and AM Frequency Procedures.

	SAS v9.1.3 PROC FREQ[1]	SAS v9.1.3 PROC FREQ	SAS v9.1.3 PROC SURVEYFREQ	SUDAAN 9.0.1 PROC CROSSTAB	AM v.0.06 FREQUENCIES
Frequency	8899	8781.15	8781	8781.15	--
Percent	41.56	41.01	41.01	41.01	41.0
SE	--	--	0.38	0.38	0.38
95% CL	--	--	(40.26, 41.75)	(40.26, 41.75)	--

[1]Estimates in this column were <u>not</u> calculated using sample weights. All other estimates in the table <u>were</u> calculated using the appropriate sample weights.

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Results from the analysis of means are presented in Table 2. As with the frequency results, the unweighted data from SAS PROC UNIVARIATE produce different means and standard deviations than those of all four weighted procedures. The weighted procedures provide identical means but the standard errors of the means produced by PROC UNIVARIATE are smaller than those produced by the three procedures that account for the complex sample in these surveys. The confidence intervals produced by SAS PROC SURVEYMEANS and SUDAAN PROC DESCRIPT are identical.

Table 2
Comparison of Results from SAS, SUDAAN, and AM Means Procedures.

	SAS v9.1.3 PROC UNIVARIATE[1]	SAS v9.1.3 PROC UNIVARIATE	SAS v9.1.3 PROC SURVEYMEANS	SUDAAN 9.0.1 PROC DESCRIPT	AM v.0.06 Descriptive
M	51.21	50.57	50.57	50.57	50.57
SD	10.34	10.01	- -	- -	- -
SE (M)	0.07	0.07	0.08	0.08	0.08
95% CL	--	--	(50.42, 50.71)	(50.42, 50.71)	--

[1]Estimates in this column were <u>not</u> calculated using sample weights. All other estimates in the table <u>were</u> calculated using the appropriate sample weights.

Results from the OLS regression analyses are presented in Table 3. As with the previous analyses, the unweighted results from SAS PROC REG differ from the results of all procedures that incorporate the sample weights. Such differences include the sample regression coefficients, standard errors, R^2 value, and the test of significance of R^2. The weighted procedures provide identical regression coefficients and R^2 values but the standard errors of the coefficients produced by PROC REG are smaller than those produced by SAS PROC SURVEYREG, SUDAAN PROC REGRESS, and AM Regression. Further, the test of significance of R^2 differs among the latter three procedures. All of the SAS procedures use a Fisher F test, the SUDAAN procedure uses a Wald F test, and the AM procedure uses an adjusted Wald F test.

Table 3
Comparison of Results from SAS, SUDAAN, and AM OLS Regression Procedures.

	SAS v9.1.3 PROC REG[1]	SAS v9.1.3 PROC REG	SAS v9.1.3 PROC SURVEYREG	SUDAAN 9.0.1 PROC REGRESS	AM v.0.06 Regression
Overall model[2]	1223.55	1001.51	1001.51	65937.59	910.21
R-Square	0.31	0.27	0.27	0.27	0.27
Estimate (SE)					
Intercept	50.17	49.85	49.85	49.85	49.85
	(0.21)	(0.21)	(0.24)	(0.24)	(0.24)
Sex	-0.38	-0.26	-0.26	-0.26	-0.26
	(0.12)	(0.12)	(0.14)	(0.14)	(0.14)
Black	-5.24	-5.37	-5.37	-5.37	-5.37
	(0.20)	(0.19)	(0.19)	(0.19)	(0.19)
Hispanic	-2.82	-2.90	-2.90	-2.90	-2.90
	(0.19)	(0.20)	(0.21)	(0.21)	(0.21)
API	2.29	1.54	1.54	1.54	1.54
	(0.25)	(0.32)	(0.34)	(0.34)	(0.34)
Indian	-3.66	-3.37	-3.37	-3.37	-3.37
	(0.31)	(0.29)	(0.31)	(0.31)	(0.31)
HW Time	1.36	1.31	1.31	1.31	1.31
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Self-concept	0.84	0.81	0.81	0.81	0.81
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
SES	4.97	4.63	4.63	4.63	4.63
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)

[1]Estimates in this column were <u>not</u> calculated using sample weights. All other estimates in the table <u>were</u> calculated using the appropriate sample weights.

[2]SAS estimates reflect the Fisher F Test, the SUDAAN estimate reflects the Wald F Test, and the AM estimate reflects the Adjusted Wald F Test.

Finally, the results from the logistic regression analyses are presented in Table 4. As with the previous analyses, the importance of the sample weights is evident in these results. Analysis of the unweighted data from SAS PROC LOGISTIC produces different log-likelihoods, chi-square statistics, pseudo-R^2 values, regression coefficients, odds ratios, and standard errors. The weighted procedures provide identical regression coefficients, odds ratios, and pseudo-R^2 values (although the AM program provides neither a pseudo-R^2 statistic nor odds ratios for the predictor variables). As with the previous analyses, the standard errors of the coefficients produced by PROC LOGISTIC are smaller than those produced by SAS PROC SURVEYLOGISTIC, SUDAAN PROC RLOGIST, and AM Logit. The test of significance of the overall model also differs for the AM procedure. All of the SAS procedures and the SUDAAN procedure use a Likelihood ratio chi-square test, and the AM procedure uses an adjusted Wald F test.

CONCLUSIONS

This paper has briefly reviewed statistical issues related to data from complex sample surveys that necessitate the use of specialized software for their analysis. Unequal probabilities of selection, multi-stage sampling, stratification, and post-stratification adjustments require special computational considerations to obtain accurate analyses of the resulting data. Using a sample of observations from the NELS88 survey, the bias resulting from a failure to include sample weights and a failure to incorporate appropriate estimates of standard errors (i.e., the naïve use of SAS PROC FREQ, PROC MEANS, PROC REG, and PROC LOGISTIC) was illustrated. Further, a comparison of results from the SAS SURVEY procedures (PROC SURVEYFREQ, PROC SURVEYMEANS, PROC SURVEYREG, and PROC SURVEYLOGISTIC) with those of analogous procedures provided by the SUDAAN and AM packages demonstrated identical results for point estimates of parameters, standard errors, confidence intervals, and hypothesis tests.

Although such identical results across software packages are reassuring, the differences across these programs should be noted. For example, the AM software package provides parameter estimates and standard errors in logistic regression that are identical to those provided by SAS and SUDAAN but provides no information about odds ratios. Conversely, both the AM and SUDAAN packages provide procedures that are not currently available in the SAS SURVEY procedures (e.g., procedures for survival analysis and generalized multinomial logit analysis). Further, the SAS procedures provide only the Taylor series linearization approach for standard error estimation (although the macro provided by Gossett and colleagues, 2002, provides a mechanism to estimate variances using replicate weights for summary statistics).

Finally, a consideration of the interfaces of these programs suggests that SAS users will find the syntax of the SAS callable SUDAAN software easy to learn. Further, the SUDAAN procedures can be invoked directly from a SAS job stream, allowing a simple interface with the power of SAS data handling. Although the stand alone AM program will import SAS data files, the program cannot be invoked directly from SAS thus requiring a separate step to write the SAS data file prior to importing. Additionally, the click-and-drag interface of the AM program is slower to use than the construction of syntax in SUDAAN or the SAS SURVEY procedures.

Table 4
Comparison of Results from SAS, SUDAAN, and AM Logistic Regression Procedures.

	SAS v9.1.3 PROC LOGISTIC[1]	SAS v9.1.3 PROC LOGISTIC	SAS v9.1.3 PROC SURVEYLOGISTIC	SUDAAN 9.0.1 PROC RLOGIST	AM v.0.06 Logit
Model fit					
-2 Log L	28083.93	28056.17	28056.17	28056.16	28056.2
Overall model[2]	988.64	933.36	933.36	933.36	88.34
R-Square	0.05	0.04	0.04	0.04	---
Estimate (SE)					
Intercept	0.75 (0.05)	0.78 (0.05)	0.78 (0.06)	0.78 (0.06)	0.78 (0.06)
Sex	0.10 (0.03)	0.07 (0.03)	0.07 (0.03)	0.07 (0.03)	0.07 (0.03)
Black	-0.52 (0.05)	-0.58 (0.05)	-0.58 (0.05)	-0.58 (0.05)	-0.58 (0.05)
Hispanic	-0.15 (0.05)	-0.20 (0.05)	-0.20 (0.05)	-0.20 (0.05)	-0.20 (0.05)
API	-0.78 (0.06)	-0.67 (0.08)	-0.67 (0.07)	-0.67 (0.07)	-0.67 (0.07)
Indian	-0.18 (0.07)	-0.20 (0.07)	-0.20 (0.08)	-0.20 (0.08)	-0.20 (0.08)
HW Time	-0.21 (0.01)	-0.21 (0.01)	-0.21 (0.01)	-0.21 (0.01)	-0.21 (0.01)
Self-concept	-0.20 (0.02)	-0.21 (0.02)	-0.21 (0.02)	-0.21 (0.02)	-0.21 (0.02)
SES	-0.11 (0.02)	-0.15 (0.02)	-0.15 (0.02)	-0.15 (0.02)	-0.15 (0.02)
OR (95% CL)					
Intercept	---	---	---	2.18 (1.95, 2.44)	---
Sex	1.10 (1.04, 1.16)	1.07 (1.01, 1.14)	1.07 (1.01, 1.15)	1.07 (1.01, 1.15)	---
Black	0.60 (0.54, 0.65)	0.56 (0.51, 0.61)	0.56 (0.51, 0.62)	0.56 (0.51, 0.62)	---
Hispanic	0.86 (0.78, 0.94)	0.82 (0.74, 0.90)	0.82 (0.74, 0.91)	0.82 (0.74, 0.91)	---
API	0.46 (0.41, 0.51)	0.51 (0.44, 0.59)	0.51 (0.44, 0.59)	0.51 (0.44, 0.59)	---
Indian	0.84 (0.72, 0.97)	0.82 (0.71, 0.94)	0.82 (0.70, 0.96)	0.82 (0.70, 0.96)	---
HW Time	0.81 (0.80, 0.83)	0.81 (0.80, 0.83)	0.81 (0.79, 0.83)	0.81 (0.79, 0.83)	---
Self-concept	0.82 (0.79, 0.85)	0.81 (0.78, 0.85)	0.81 (0.78, 0.86)	0.81 (0.78, 0.86)	---
SES	0.90 (0.86, 0.93)	0.86 (0.83, 0.89)	0.86 (0.82, 0.90)	0.86 (0.82, 0.90)	---

[1]Estimates in this column were <u>not</u> calculated using sample weights. All other estimates in the table <u>were</u> calculated using the appropriate sample weights.

[2]Estimates in this row are Likelihood Ratio Chi-Square values, except for the estimate provided by AM, which is the Adjusted Wald F Test.

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