

# Software Alternatives for Variance Estimation in the Analysis of Complex Sample Surveys: A Comparison of SAS Survey Procedures, SUDAAN, and AM

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## Abstract

The use of standard statistical software for the analysis of data collected from complex sample surveys 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 (e.g., Taylor series approximations or replication estimates). This paper provides a review of the special statistical requirements for the analysis of complex survey data; a comparison of a sample of available statistics and variance estimation strategies provided in SAS, SUDAAN SAS-Callable, and AM; and a contrast of results across these packages. The paper includes samples of code and illustrations of partial output from each software package.

**KEY WORDS:** Complex sample surveys, variance estimation, software comparison

## 1. Introduction to Complex Sample Surveys

Over the last few decades, secondary data analysis of large, nationally representative complex sample surveys has become more common among social and behavioral scientists. Given its many benefits, it is not surprising that the use of such data has become common place across a variety of disciplines. Practical benefits of conducting secondary data analysis of complex surveys include the notion that doing so is often more cost effective than collecting primary data and secondary data are typically easier to obtain than primary data (Hofferth, 2005; Rosenberg, Greenfield, & Dimick, 2006). Statistical benefits of large, complex surveys include large sample sizes, the vast array of variables, and increased power and generalizability due to the population representativeness of the data (Hofferth, 2005; McCall & Applebaum, 1991; Rosenberg, Greenfield, & Dimick, 2006). Also, the longitudinal nature of many complex surveys allows researchers the opportunity to investigate research questions that could not be addressed with primary, cross-sectional data.

However, just as there are benefits when using complex sample survey data in social and behavioral science research, there are also drawbacks associated with this type of data. Not only were the data collected for purposes other than the purpose of the secondary analysis, but the time associated with learning about the data including survey items, data structure, and technical documentation can be extensive (Hofferth, 2005; McCall & Applebaum, 1991). Data quality, including missing data, the operationalization of latent constructs, and the quality of supporting documentation are also important methodological limitations of using data from large, complex surveys (McCall & Applebaum, 1991; Rosenberg, Greenfield, & Dimick, 2006). Lastly, contrary to primary research, the data often dictate research questions when conducting secondary data analysis which is opposite of the traditional methods most researchers learned as graduate students (Hofferth, 2005; McCall & Applebaum, 1991).

## 1.1 Sources of Complex Sample Survey Data

Complex social science survey data are available through a variety of archives including the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan, National Center for Health Statistics (NCHS), and National Center for Education Statistics (NCES). Being the world's largest repository and dissemination service of social science data (Kiecolt & Nathan, 1985), ICPSR data sources are stored in 15 archives, arranged by topic area. Example archives include General Social Survey Data, Health and Medical Care Archive, and National Archive of Criminal Justice Data (ICPSR, n.d.). Although NCHS and NCES also provide numerous complex sample survey data sources, unlike the ICPSR, they are discipline specific. NCHS provides health-related data sources [e.g., National Health and Nutrition Examination Survey, National Survey of Early Childhood Health, National Immunization Survey (Centers for Disease Control and Prevention, 2004)] and NCES offers education-related data sources [e.g., National Household Education Survey, Common Core of Data, Early Childhood Longitudinal Study (NCES, n.d.a.)].

## 2. Background on Complex Sample Surveys

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

### 2.1 Sample Weights

Typically, observations from complex sample surveys are weighted such that each observation's weight is equal to the reciprocal of its selection probability. 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)

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

To obtain unbiased parameter estimates, the weights are applied in the computation of statistics from the sample observation. For example, the sample mean is computed as

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

### 2.2 Estimation of Variances

The accurate estimation of sampling error is a critical

component of complex 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 data obtained from complex sample surveys (involving stratification, multi-stage sampling, and unequal probabilities of selection) the calculation of sampling error differs from that used in simple random sampling. Unfortunately, software designed for general data analysis calculates standard errors under the assumption of simple random sampling. A variety of methods are available for appropriate estimation of sampling error, including Taylor series 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 observed data, 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 brings 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 take repeated subsamples from the observed data, calculate the desired statistic in each subsample, and estimate the variance of the statistic by computing the variance of the subsample values. The different methods included 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 addition to the linearization and replication approaches, many surveys also provide estimates of design effects (DEFFs) that may be used to adjust the sampling error calculated by techniques and software that assume simple random sampling. The DEFF is 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 complex sample surveys and estimates 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.

### 3. Software Options for Complex Sample Survey Analysis

Researchers conducting secondary data analysis using complex survey data have several statistical software options 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, three commonly used software packages for analysis of complex sample survey data are the SAS SURVEY procedures, SUDAAN SAS-Callable, and AM. The following sections provide brief descriptions of the available statistics and the methods for variance estimation for each of the three statistical programs.

#### 3.1 SAS v9.1.3

Users of the SAS statistical software package can take into account the complex sampling design of large-scale surveys by using the set of SURVEY procedures available in the SAS/STAT package (provided in version 7 and higher). All four of the available SAS SURVEY procedures (i.e., SURVEYMEANS, SURVEYREG, SURVEYFREQ, and SURVEYLOGISTIC) use the Taylor series linearization approach to estimate sampling errors (SAS Institute Inc., 2004). In addition to the SAS SURVEY procedures, analysis of large-scale data sets that include replicate weights is provided through a macro to calculate weighted variance estimates for summary statistics (mean and median) and

corresponding standard errors using JK2 estimates (Gossett, Simpson, Parker, & Simon, 2002).

The SAS SURVEY procedures require the same syntax as other SAS procedures (e.g., 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 SURVEYLOGISTIC and partial output from the procedure is provided in Figure 1.

```
proc surveylogistic data = babe.amjism;
strata pstratum;
cluster ppsu;
weight fpwt;
model suspended (event = last) = commun
nocmprules nocomp tvrules schact gender age grades/ rsq;
title 'SAS SURVEYLOGISTIC';
run;
```

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr>Chisq
Intercept	1	-6.428	0.439	214.788	<.0001
commun	1	0.356	0.112	10.185	0.0014
nocmprules	1	-0.092	0.125	0.539	0.4629
nocomp	1	0.678	0.117	33.283	<.0001
tvrules	1	0.070	0.102	0.470	0.4928
schact	1	0.282	0.088	10.251	0.0014
gender	1	-0.691	0.086	64.373	<.0001
age	1	0.188	0.014	173.742	<.0001
grades	1	0.703	0.047	221.734	<.0001

Figure 1: SAS syntax and partial output

#### 3.2 SUDAAN SAS9-Callable 9.0.1

The current SUDAAN software package, developed with advice and assistance from the SAS Institute, evolved from a single general survey analysis procedure in SAS (STDERR, Research Triangle Institute, 2004). The SUDAAN package was specifically created in response to the need for software that could appropriately calculate variance estimates for data from complex sample surveys. The most recent release of 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 SAS-Callable 9.0.1 include: CROSSTAB, RATIO, DESCRIPT, REGRESS, LOGISTIC, MULTILog, LOGLINK, SURVIVAL, and KAPMEIER (Research Triangle Institute, 2004).

The SUDAAN SAS-Callable procedures use syntax similar to that of SAS (e.g., DATA =, VAR, TABLE, MODEL, and WEIGHT). An example of SUDAAN

syntax for PROC RLOGIST and partial output from the procedure is provided in Figure 2.

```
proc RLOGIST data=readynow design=jackknife filetype=sas;
weight fpwt;
jackwghts fpwt1 --fpwt80/adjjack = 1;
MODEL suspended = commun nocmprules nocomp tvrules schact gender age grades;
TITLE " " "SUDAAN RLOGIST" " " ;
run;
```

Independent Variables and Effects	Beta Coeff.	SE Beta	Lower 95% Limit Beta	Upper 95% Limit Beta	T-Test B = 0	P-value T-Test B = 0
Intercept	-6.43	0.41	-7.25	-5.61	-15.61	0.0000
commun	0.36	0.11	0.13	0.58	3.16	0.0022
nocmprules	-0.09	0.13	-0.34	0.16	-0.72	0.4712
nocomp	0.68	0.12	0.45	0.91	5.82	0.0000
tvrules	0.07	0.11	-0.15	0.29	0.63	0.5292
schact	0.28	0.08	0.11	0.45	3.33	0.0013
gender	-0.69	0.08	-0.86	-0.52	-8.28	0.0000
age	0.19	0.01	0.16	0.22	13.50	0.0000
grades	0.70	0.05	0.61	0.79	15.32	0.0000

Figure 2: SUDAAN SAS-Callable syntax and partial output

### 3.3 AM v.0.06

Originally produced 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.). Currently, AM is in a Beta release version and includes several 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 use a Taylor series approximation to estimate standard errors. However, use of Jackknife estimation is available for some procedures.

Unlike the SAS and SUDAAN SAS-Callable packages, AM 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 logistic regression input and the html output from this procedure in AM.

## 4. Comparison of Statistical Results

Data from the 2003 National Household Education Survey (NHES, NCES, n.d.b.) were used to compare point estimates and standard errors obtained from SAS, SUDAAN SAS-Callable, and AM for four commonly used analytic techniques - frequencies, means, OLS regression, and logistic regression. Each statistical technique was estimated through the relevant weighted SAS SURVEY procedure using Taylor series linearization for variance estimation and through the relevant weighted SUDAAN SAS-Callable and AM procedures using Jackknife replication methods for variance estimation. Frequencies were analyzed for a student suspension indicator variable (yes/no) created from the NHES data and means were analyzed for students' average grades across all subjects. Both the OLS (predicting student average grades) and logistic regression (predicting student suspension) models contained a mixture of eight continuous and dichotomous regressors, including the child's gender and age, the presence of household rules about television and computer use, and measures of parent-child communication and parental involvement in school activities.

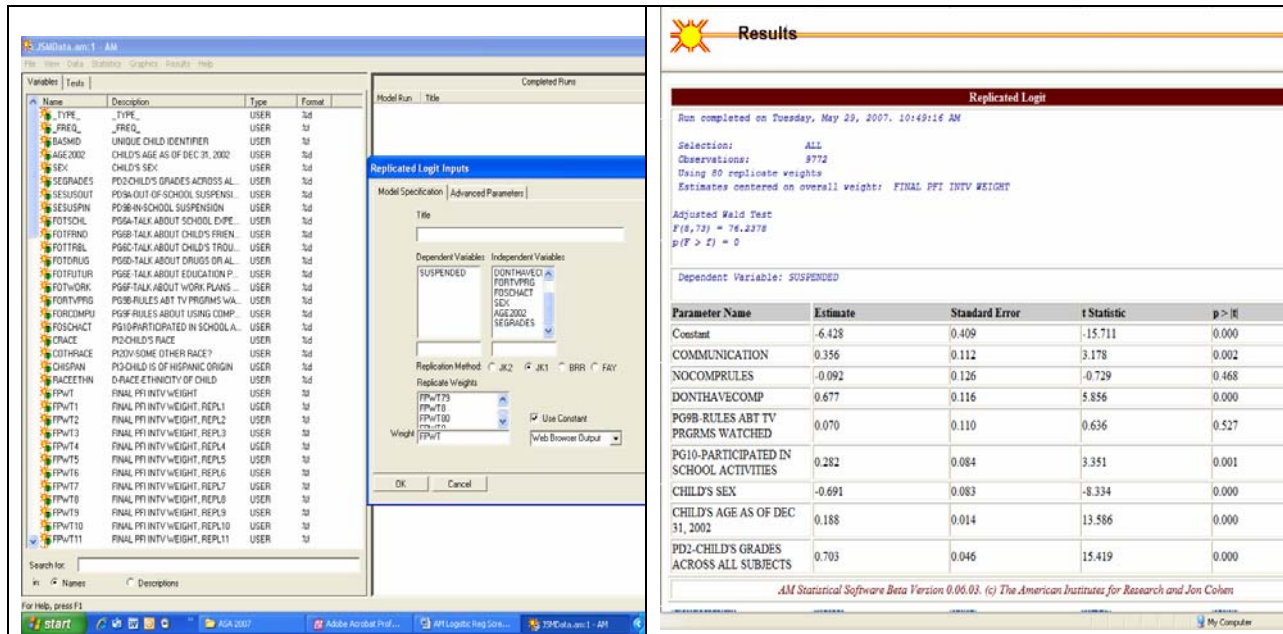


Figure 3: AM input and output

Results from the analysis of frequencies are presented in Table 1. The results from procedures in all three software programs provided identical percentages (except for a different rounding level for the AM program). Standard errors of the percentages provided by SUDAAN PROC CROSSTAB and AM

were also identical. However, the standard error of the percentage from SAS PROC SURVEYFREQ and the Taylor series linearization was slightly larger than those provided by SUDAAN and AM. The 95% CI provided by SAS was also slightly larger than that provided by SUDAAN. The AM program does not provide confidence intervals around frequencies.

Table 1: Comparison of Results from SAS, SUDAAN, and AM Frequency Procedures for Student Suspension<sup>1</sup>

	SAS v9.1.3 PROC SURVEYFREQ	SUDAAN 9.0.1 PROC CROSSTAB	AM v.0.06 FREQUENCIES
Frequency	1228	1228	--
Percent	12.57	12.57	12.60
SE	.43	.41	.41
95% CL	(11.73 ,13.41)	(11.78 ,13.40)	--

<sup>1</sup>SAS estimates were calculated using Taylor series linearization. SUDAAN and AM estimates were calculated using Jackknife replication methods.

Results from the analysis of means are presented in Table 2. As with the frequency results, the three procedures provided identical means (except for a different rounding level from AM). However, unlike the frequency results, the standard errors of the means were the same across variance estimation methods. Similarly, the 95% CI produced by SAS PROC SURVEYMEANS and SUDAAN PROC DESCRIBE were identical. The AM program does not produce confidence intervals around the mean.

the test of significance of  $R^2$  differs among the three procedures. SAS used a Fisher  $F$  test, the SUDAAN procedure used a Wald  $F$  test, and the AM procedure used an adjusted Wald  $F$  test. Also, the regression coefficients were the same across procedures (except for a different rounding level for the AM program for one regressor) and all but one of the standard errors were the same.

Results from the OLS regression analyses are presented in Table 3. All three procedures (SAS PROC SURVEYREG, SUDAAN PROC REGRESS, and AM OLS) produced identical  $R^2$  values, however

Finally, the results from the logistic regression analyses are presented in Table 4. As with the previous analyses, the two variance estimation methods produced identical point estimates; however, several of the standard errors for variables in the model using Taylor series linearization (SAS PROC

SURVEYLOGISTIC) were slightly different than those generated by the Jackknife replication estimation methods in SUDAAN and AM. Interestingly, sometimes the standard errors generated from SAS PROC SURVEYLOGISTIC were slightly smaller than the standard errors from SUDAAN PROC RLOGIST and AM logit and sometimes they were slightly larger. Similarly, some of the odds ratios for the predictor variables generated in SAS were slightly different than those

created in SUDAAN (AM does not provide odds ratios as part of the logistic regression output). The AM logit procedure also does not estimate model fit, nor does it create a pseudo- $R^2$ . The test of significance of the overall model also differs for the AM procedure. The SAS procedure and the SUDAAN procedure use a Likelihood ratio chi-square test, and the AM procedure uses an adjusted Wald  $F$  test.

Table 2: Comparison of Results from SAS, SUDAAN, and AM Means Procedures Student Grades<sup>1</sup>

	SAS v9.1.3 PROC SURVEYMEANS	SUDAAN 9.0.1 PROC DESCRIPT	AM v.0.06 Descriptive
M	1.79	1.79	1.80
SD	--	--	0.83
SE (M)	0.01	0.01	0.01
95% CL	(1.77, 1.82)	(1.77, 1.82)	--

<sup>1</sup>SAS estimates were calculated using Taylor series linearization. SUDAAN and AM estimates were calculated using Jackknife replication methods.

Table 3: Comparison of Results from SAS, SUDAAN, and AM OLS Regression Procedures Predicting Student Grades<sup>1</sup>

	SAS v9.1.3 PROC SURVEYREG	SUDAAN 9.0.1 PROC REGRESS	AM v.0.06 Regression
Overall model <sup>2</sup>	202.83	4310.65	115.25
R-Square	.14	.14	.14
Estimate (SE)			
Intercept	1.05 (0.10)	1.05 (0.10)	1.06 (0.10)
Parent-Child Communication	0.07 (0.03)	0.07 (0.03)	0.07 (0.03)
Computer Rules	-0.08 (0.03)	-0.08 (0.03)	-0.08 (0.03)
No Computer	0.24 (0.03)	0.24 (0.04)	0.24 (0.04)
T.V. Rules	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
School Activities	0.22 (0.02)	0.22 (0.02)	0.22 (0.02)
Ever Suspended	0.50 (0.03)	0.50 (0.03)	0.50 (0.03)
Gender	-0.23 (0.02)	-0.23 (0.02)	-0.23 (0.02)
Age	0.04 (0.01)	0.04 (0.01)	0.04 (0.01)

<sup>1</sup>SAS estimates were calculated using Taylor series linearization. SUDAAN and AM estimates were calculated using Jackknife replication methods.

<sup>2</sup>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.

Table 4: Comparison of Results from SAS, SUDAAN, and AM Logistic Regression Procedures Predicting Student Suspension<sup>1</sup>

	SAS v9.1.3 PROC SURVEYLOGISTIC	SUDAAN 9.0.1 PROC RLOGIST	AM v.0.06 Logit
Model fit			
-2 Log L	6238.04	6238.04	--
Overall model <sup>2</sup>	1151.24	1151.24	76.24
R-Square	0.11	0.11	--
Estimate (SE)			
Intercept	-6.43 (0.44)	-6.43 (0.41)	-6.43 (0.41)
Parent-Child Communication	0.36 (0.11)	0.36 (0.11)	0.36 (0.11)
Computer Rules	-0.09 (0.12)	-0.09 (0.13)	-0.09 (0.13)
No Computer	0.68 (0.12)	0.68 (0.12)	0.68 (0.12)
T.V. Rules	0.07 (0.10)	0.07 (0.11)	0.07 (0.11)
School Activities	0.28 (0.09)	0.28 (0.08)	0.28 (0.08)
Student Grades	0.70 (0.05)	0.70 (0.05)	0.70 (0.05)
Gender	-0.69 (0.09)	-0.69 (0.08)	-0.69 (0.08)
Age	0.19 (0.01)	0.19 (0.01)	0.19 (0.01)
OR (95% CL)			
Intercept	--	0.00 (0.00, 0.00)	--
Parent-Child Communication	1.43 (1.15, 1.78)	1.43 (1.14, 1.79)	--
Computer Rules	0.91 (0.72, 1.17)	0.91 (0.71, 1.17)	--
No Computer	1.97 (1.56, 2.48)	1.97 (1.56, 2.48)	--
T.V. Rules	1.07 (0.88, 1.31)	1.07 (0.86, 1.34)	--
School Activities	1.33 (1.12, 1.58)	1.33 (1.12, 1.57)	--
Student Grades	2.02 (1.84, 2.22)	2.02 (1.84, 2.21)	--
Gender	0.50 (0.42, 0.59)	0.50 (0.42, 0.59)	--
Age	1.21 (1.17, 1.24)	1.21 (1.17, 1.24)	--

<sup>1</sup>SAS estimates were calculated using Taylor series linearization. SUDAAN and AM estimates were calculated using Jackknife replication methods.

<sup>2</sup>Estimates in this row are Likelihood Ratio Chi-Square values, except for the estimate provided by AM, which is the Adjusted Wald *F* Test.

## 5. Conclusions

This paper has briefly reviewed the statistical issues associated with data from complex sample surveys that necessitate the use of specialized software for their analysis. The presence of unequal probabilities of selection, multi-stage sampling, stratification, and post-stratification adjustments require appropriate computational considerations to allow accurate analyses of the resulting data. Using a sample of observations from the NHES data, a comparison of results from the SAS SURVEY procedures (using Taylor series approximations for variance estimates) with those of analogous procedures provided by the SUDAAN SAS-Callable and AM packages (using Jackknife replication procedures) demonstrated identical results for point estimates of parameters, and only minor differences in standard errors and

confidence intervals. A previous comparison of the Taylor series solutions from these three statistical packages indicated identical results for standard errors, confidence intervals, and hypothesis tests (Bell-Ellison & Kromrey, 2007).

Although such nearly identical results across the software packages and across variance estimation techniques 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 but provides no information about odds ratios. The lack of estimates of odds ratios and associated confidence intervals is a major limitation because these statistics are frequently interpreted in logistic analyses. Conversely, both the AM and SUDAAN SAS-Callable packages provide procedures that are not

currently available in the SAS SURVEY procedures (e.g., procedures for survival analysis and generalized multinomial logit analysis).

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. Additionally, 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. Further, the click-and-drag interface of the AM program is slower to use than the composition of syntax in SUDAAN SAS-Callable or the SAS SURVEY procedures.

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