ANALYTIC LIMITATIONS TO CURRENT NATIONAL HEALTH SURVEYS

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1. Introduction

National health surveys, as conducted by the Centers for Disease Control's (CDC) National Center for Health Statistics (NCHS), are usually designed to meet analytic criteria based on specified levels of precision for simple, descriptive estimates. For example, the National Health Interview Survey (NHIS) is designed to produce highly reliable estimates of health related characteristics of the civilian noninstitutionalized population of the United States. The NHIS is a complex, multistage probability sample, and a technical discussion appears in Massey et al. (1989). The survey is conducted weekly at the national level, and annual estimates are published in NCHS Current Estimates Series 10 reports (for example, see Moss and Parsons (1985)).

The complexity of the NHIS and the lack of a comprehensive software package for complex-survey data have forced researchers to analyze the NHIS data under simplified design structures. Some of the imposed design structures are reasonable, but others may lead to invalid inference. In this paper we consider some of the simplified structures that we have observed in practice and, for the benefit of users of NHIS data, consider some limitations imposed by simplified design structures.

In addition to the simple descriptive statistics, the NHIS data are being used more for detailed analysis, often using regression or analysis of variance techniques. Comparisons of subdomains, e.g., black vs white or male vs female, are usually analytic objectives. In preparing estimates for subdomains, data users may prepare a subset of the original survey data file and then create first- and second-order estimates from the subset file. Problems may arise if the survey design is ignored in creating these smaller data files. In this paper we show how subsetting data affects the computation of standard errors.

Users of NHIS data often observe that the large dispersion among sampling weights results in a few sample individuals being highly influential when estimates over small subdomains are produced. We consider the impact of the disparity among the sampling weights upon estimation.

2. Inefficient modeling of NHIS design structure

In the past, the software written for complex-survey designs often used methodology which assumed that two primary sampling units (PSUs) were sampled from each stratum with replacement. Even though newer software (e.g., SUDAAN, PC-CARP, and WESVAR) can make use of a more complicated design structure, many users are often tempted to impose a "two sample PSUs with replacement" model. If this is done, the actual without replacement sampling methodology within the non-self-representing (NSR) strata is ignored. Furthermore, to accommodate the simplified model, the survey self-representing (SR) strata are often split into two Pseudo-PSUs. This practice usually results in a loss of efficiency on the SR sampling component.

Another feature of complex designs is the ratio-adjustment on the sampling weights. The NHIS provides each sample person with a ratio-adjusted final weight, defined so that NHIS age-sex-race totals agree with current estimates from the U.S. Bureau of the Census. Many users simply treat this final weight as if it were a basic selection weight, i.e., the inverse of a probability of selection. By doing so, the variance reduction and/or increase due to the adjustment procedures is ignored.

We have examined some of these issues with respect to the 1987 NHIS by considering three design structures, Model(1), Model(2) and Model(3), as outlined in Table 1. Some limitations to the modeling are

1. The Second Stage Units (SSUs) are treated as though sampled with replacement. Population counts are not readily available, but the sampling fraction is small. In reality the sampling of SSUs is systematic in nature.

2. The non-response adjustment and NSR adjustment weights are absorbed into the base weight.

3. Only models admissible to the SUDAAN software are considered.

Limitation 1, the treatment of the sampling of SSU's as with replacement will probably lead to a slightly inflated estimator of variance. Limitation 2 will probably have little impact (see Parsons and Casady 1987). Limitation 3 is not severe, as SUDAAN was developed with nested, multi-stage surveys in mind. The SUDAAN software uses a Taylor-linearization approach. It will accommodate unequal probabilities of selection at first-stage sampling, and simple random sampling without replacement at second and higher stages. Poststratification can be utilized for variance estimation.

Model(1) represents our "best" representation of the actual NHIS design subject to the above constraints, and also incorporates the poststratification-adjustment into variance estimation. Model(2) is the same as Model(1) except that the final weight is treated as a base weight, i.e., the first-order estimators will incorporate all the adjustments, but estimators of standard errors will will use the base-weight methodology with the final poststratified adjusted weights. Model(3), which basically assumes sampling with replacement at the first-stage, and no compensation for poststratification in variance estimation, is the simplified design structure commonly applied by users of NCHS data tapes.

2.1 Comparisons among the three design models

The analytic variables considered are listed in Table 2. The variables for month of birth provide a standard. These variables should be uncorrelated with the design and should have roughly the same sampling distributions. We also considered both the 1987 NHIS Core and Supplement as data sets of interest. For the Core all persons within a SSU are targeted for sample, but for the Supplement, one sample adult is selected from each household within a sample SSU, (see Massey et al. (1989)).

Because Model(1) is considered to be our "best" design model for variance estimation, the ratios of Standard Errors (SEs) :

R(2,1) = SE(Model(2)) / SE(Model(1)) and

R(3,1) = SE(Model(3)) / SE(Model(1))

will provide measures of comparison.

The cost of computing SE's on large data sets is often a major factor in choosing a design model. The relative required CPU time for Models (1),(2) and (3) is approximately 8:2:1. Incorporating a poststratification adjustment by 60 age-sex-race groups for the NHIS is by far the most expensive. Thus, if for a wide range of variables, R(k,1) is close to 1.0 for k = 2 or 3, then Model(k) might be considered for analysis if software limitation or computer cost is a major constraint.

The ratios R(k,1) depend upon the type of estimator used. Since most of the estimates produced by NCHS are weighted totals, i.e., the aggregate of sample measurements inflated by the survey weight, or means and proportions, i.e., the ratio of a weighted totals, the current study will only be concerned with such statistics.

In Figure 1 the values of R(2,1) and R(3,1) are plotted for Core sample estimates of SE of total on selected sex and racial subdomains for ages 18-64. The x-axis "VARIABLE ID" labels are defined in a cyclic fashion using the ID's of Table 2, e.g., ID's 2,13 and 24 represent the same variable. It can be seen that using Model(2) or Model(3) may result in the overinflation of SE's. On the Black subdomains the SE's were quite large. The estimate for Black Females with health status fair or poor (variable id 36) was 1,736,000 and the SE using Model(1) was 55,000, but the inflations of SE using Models (2) and (3) are 1.63 and 1.94, respectively. Model(3) SE's tend to be larger than Model(2) SE's. We do not recommend either Model(2) or Model(3) for the estimation of SEs of totals.

For estimating SE's of means or proportions, Model(2) fares quite well compared with Model(1). For the Core sample, the SE computed under Model(2) tends to be within 5% of Model(1)'s estimate, however, Model(3)'s estimate tends only to be within 15%. In either case, the estimate of SE may be larger or smaller than Model(1)'s estimated SE. Now, for a given mean, expressed as the ratio of two estimated totals, X/Y, with the denominator Y an aggregate of poststratification cells, we have the approximation:

$$R^2(k,1) =$$

$$[CV^2(X:k) - 2r_k CV(X:k)CV(Y:k) + CV^2(Y:k)]/CV^2(X:1)$$

where $CV(X:k)$ = coefficent of variation of X, and r_k = correlation X and Y under Model(k)

A lower bound of the above expression is

$$[\ CV(X:k) - CV(Y:k)\ ]^2 \ / \ CV^2(X:1)$$

which certainly can be less than 1. So estimating R(k,1) less than 1 is not surprising. Furthermore, the estimated ratio R(k,1) is also subject to sampling error. Figure 2 compares the ratios R(2,1) and R(3,1) for means and proportions for the same variables and subdomains listed in Figure 1. In general, it appears that the use of Model(2) will provide reasonable estimates of SE for means and proportions and requires only 1/4 of the CPU time of Model(1).

The Supplement sample results are similar, but there is a greater deviation from Model(1). In this sample additional variability is introduced into the system by the subsampling within households within the sample SSU's. All the Models now lead to more variable estimators of SE. In Figure 3 the values of R(2,1) and R(3,1) are plotted for the same mean and proportion variables and on the subdomains as in Figure 2. Here, Model(2)'s SE tends to be within 7% of Model(1)'s SE, but Model(3) can produce a SE inflated by 20%. For the Supplement we still feel that Model(2) is a viable option for analysis for means and proportions.

3. Examination of the Effect of Subsetting Data

Analysts who are only interested in a particular subdomain, e.g., persons aged 65+, often create a data file containing only that subdomain. Analyses are then performed using the abbreviated data set. This type of data reduction often destroys the integrity of the sample design. While the first-order estimators, e.g., totals, means and ratios, are not affected, the estimators of variance may be adversely affected.

For our study we created two subsetted files from the Core NHIS: the Black sample and the Aged 65+ sample. For the Black sample both PSU's and SSU's were lost, i.e., the units had no sample of interest. For the Aged 65+ sample only PSU's were lost. Because Black or Aged 65+ is a measured characteristic, the "lost" units from the subsetted data set should really be recorded as a measurement of zero and the unit kept. If Model(1) or Model(2) is used when estimating SE's, then the sample SSU counts and sum of squared deviations will be computed over a restricted set. Thus the correct estimator of SSU variance will not be used. Since our survey sampled two PSUs per stratum, a lost PSU requires a "fixup". SUDAAN uses the sample population mean value to "pair-up" solo sampling units (see SUDAAN (1989)). Unlike SUDAAN, other computer software may terminate execution if only one PSU in a stratum is identified in the input data set. The analyst must determine a corrective action. If data must be subsetted, dummy records should be added to preserve the full design. The nature of the dummy records, of course, depends upon the software to be utilized. With SUDAAN the dummy records need only design variables. Model(1) or (2) can then be used.

For our study we assumed that analysts who subset data without preserving the integrity of the design will most likely use Model(3) in their analyses, and thus we have only considered that model. In Figures 4 and 5 we present the ratio R(3,1) computed for the respective subsetted files Aged 65+ and Black; Model(1) was implemented on a data file which preserved the integrity of the sample design. Model(3) on the subsetted data fares poorly. Because of smaller sample sizes, greater variability in SE's can be expected. For this example, SE inflation and deflation in the 10% range tend to be typical. For the Black subset subdomain of 18-64 the SE of mean hospital episode days (variable id 33) was inflated by 30%.

4. Influence of Weights

The 1985-1994 NHIS design is not self-weighting, i.e., the weight defined by the product of the inverses of probability of selection of the ultimate sampling unit is not a design constant. To improve the precision of estimators over Black subdomains, areas of high concentration of the Black population are oversampled. While this sampling strategy allowed for a much larger Black sample size, gains in precision are curbed somewhat by a larger sampling weight variability. It should be noted that when studying the Black subdomains, Blacks in oversampled areas have small weights, while Blacks in undersampled areas have large weights. For national estimators, the subjects with extreme sampling weights have little influence, but for smaller subdomains their inclusion may have a pronounced affect on an estimator. Not only can a sample person have a large (or small) sampling weight, but a sample person can also have a large (or small) analytic variable. Obviously, an influential observation can occur in either situation, but especially when a sample person has both a large weight and a large value.

One measure of the influence of the weights is the change in the first- and second-order estimate when the sampling weights are truncated. A change to the weights results in changes in estimator bias and variance. Decreases in estimated variance may be countered by increases in unobservable bias.

Because information on the population universe is not available, our study of influence is limited in scope. One simple way to evaluate the influence of the weights is to consider variables "uncorrelated" with the design. Here, we use the term "uncorrelated" in the super-population setting: suppose that to each individual in the population is generated a random variable Z, and the Z's are independent and identically distributed among all population persons.

To minimize the mean squared error of a statistic

$\Sigma w Z / \Sigma w$ (with Z having mean E(Z) and variance V(Z))

one would use a self-weighting design. Furthermore, there is no bias due to selection of weights.

To use such a super-population model on the NHIS, we treated the NHIS variable "month of birth" as a multinomial random variable generated by nature independent and identically distributed from person to person. We considered the coefficient of variation (CV) for percentage of persons born in each of 11 months (August was excluded because in 1987 missing observations were imputed to that month on the data tape) computed using original design weights and also computed with unweighted data. The estimated CVs for each month should have similar sampling distributions within each weighing scheme. This was done for both the Core and the Supplement surveys. Summary statistics are produced in Tables 3 and 4. For the Core, we see that for large subdomains the use of unweighted data reduces the CV by 5-7%, while on Black subdomains the reduction is about 12%. For the Black subdomains a large reduction is to be expected because the heterogeneity of the sampling weights increases the CV.

For "month of birth" percentages both weighted an unweighted estimators should be unbiased, thus we have a measure of influence of the weights. For the Supplement data the effect of the weighting is even more pronounced. The CVs for large subdomains is about 12% larger for weighted data than unweighted data and about 20% larger on the Black subdomains.

For Health characteristics a change of weight introduces a bias as well as affecting SE. Comparing unweighted vs weighted estimates would be of little utility without a good measure of bias. We considered a mild truncation of sampling base weights (no Poststratification) with the hope of introducing little bias. The upper 1% NHIS core base weights were truncated to the 99% percentile weight. Comparisons were made between the first- and second-order estimates under the two weighting schemes. In Table 5, effects of truncation on four estimates of mean over several subdomains is given. Three measures of change used are:

(1) ratio of first-order estimate(truncated) to first-order estimate(original)

(2) ratio of SE estimate (truncated) to SE estimate (original)

and a measure of total change

(3) $\text{sqrt}\{ [1\text{-meas}(1)]^2 + [1\text{-meas}(2)]^2 \}*100$

For our truncation we see that the change to the first-order estimate is small, measure(1) at most represents a 5% change, but most change is no more than 1%. The change in the estimated SE's is more pronounced. Black and Non Black, Non White (specified NBW in Table 5) subdomains have large reductions in SE. Currently, we do not have a general, uniform recommendation on truncation. We do, however, recommend that the data of interest be examined for combined impact of sampling weight and value. In terms of "outlier" detection, case deletion and/or value/weight truncation can be examined for its impact.

5. References

Massey, J.T., Moore, T.F., Parsons, V.L., Tadros W., (1989) Design and estimation for the National Health Interview Survey, 1985-94. National Center for Health Statistics. Vital Health Stat 2(110).

Moss A.J. and V.L. Parsons (1985): National Center for Health Statistics, Current estimates from the National Health Interview Survey, 1985. Vital and Health Statistics. Series 10, No. 160

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Table 1. DESIGN MODELS USED FOR 1987 NHIS VARIANCE ESTIMATION

MODEL	SAMPLING HIERARCHY	SELECTION OF UNITS	WEIGHTING AND POSTSTRATIFICATION
(1)	Stratum $\supseteq$ PSU Substratum $\supseteq$ SSU	NSR PSUs selected : with known joint probabilities SSUs selected with replacement within within Substrata	Base weights with linearization for Poststratification adjustment weights
(2)	same as Model (1)	same as Model (1)	Final Poststratification absorbed into base weight (no linearization for Poststratification)
(3)	Stratum $\supset$ Pseudo-PSU	NSR PSUs selected with replacement SR PSUs split into 2 or 4 Pseudo-PSUs	same as Model (2)

Table 3 INFLUENCE OF DESIGN WEIGHTS ON THE COEFFICIENT OF VARIATION FOR A CHARACTERISTIC WHICH IS UNCORRELATED WITH THE NHIS DESIGN

CHARACTERISTICS - PERCENTAGE OF PERSONS BORN IN A GIVEN MONTH FOR 11 MONTHS

NHIS CORE - ALL SAMPLE PERSONS PER HOUSEHOLD

SUBDOMAIN AGE	RACE	SEX	HISPANIC	SAMPLE SIZE	MEAN WGTD CV	MEAN UNWGTD CV	MEAN RATIO CV's
ALL	.	.	.	122859	1.0	1.0	1.07
.	.	M	.	58411	1.5	1.4	1.05
.	.	F	.	64448	1.4	1.3	1.07
.	W	.	.	99626	1.1	1.1	1.05
.	W	M	.	47894	1.6	1.5	1.04
.	W	F	.	51732	1.6	1.5	1.05
.	B	.	.	19633	2.7	2.4	1.12
.	B	M	.	8779	4.0	3.6	1.10
.	B	F	.	10854	3.6	3.2	1.12
.	O	.	.	3600	6.1	5.7	1.08
.	O	M	.	1738	9.0	8.2	1.10
.	O	F	.	1862	8.6	8.0	1.08
.	.	.	HISP	9463	3.6	3.5	1.04
.	.	M	HISP	4569	5.2	5.0	1.05
.	.	F	HISP	4894	5.0	4.8	1.04
0-17	.	.	.	34625	1.9	1.8	1.07
0-17	.	M	.	17766	2.7	2.5	1.05
0-17	.	F	.	16859	2.8	2.6	1.08
0-17	W	.	.	26536	2.2	2.1	1.05
0-17	W	M	.	13629	3.0	2.8	1.04
0-17	W	F	.	12907	3.2	3.0	1.06
0-17	B	.	.	6998	4.4	4.0	1.11
0-17	B	M	.	3569	6.0	5.6	1.07
0-17	B	F	.	3429	6.5	5.8	1.12
0-17	O	.	.	1091	11.3	10.4	1.09
0-17	O	M	.	568	16.4	15.0	1.09
0-17	O	F	.	523	16.0	15.2	1.06
18-64	.	.	.	73683	1.3	1.2	1.07
18-64	.	M	.	34715	1.9	1.8	1.05
18-64	.	F	.	38968	1.8	1.7	1.06
18-64	W	.	.	60432	1.4	1.3	1.05
18-64	W	M	.	29101	2.0	1.9	1.04
18-64	W	F	.	31331	2.0	1.9	1.05
18-64	B	.	.	10933	3.6	3.3	1.11
18-64	B	M	.	4530	5.5	5.0	1.10
18-64	B	F	.	6403	4.7	4.2	1.11
18-64	O	.	.	2318	7.5	7.0	1.07
18-64	O	M	.	1084	11.0	10.1	1.08
18-64	O	F	.	1234	10.4	9.5	1.10
65+	.	.	.	14551	3.0	2.8	1.06
65+	.	M	.	5930	4.7	4.4	1.07
65+	.	F	.	8621	3.8	3.6	1.07
65+	W	.	.	12658	3.1	3.0	1.04
65+	W	M	.	5164	4.9	4.8	1.04
65+	W	F	.	7494	4.0	3.8	1.05
65+	B	.	.	1702	9.1	8.2	1.10
65+	B	M	.	680	14.3	12.9	1.11
65+	B	F	.	1022	11.5	10.5	1.09
65+	O	.	.	191	27.9	25.5	1.11
65+	O	M	.	86	42.6	39.5	1.09
65+	O	F	.	105	38.1	35.2	1.09

Table 2: VARIABLES USED IN ANALYSIS

ID	Name	Definition
1	dr2y	number or proportion of persons who have not seen a doctor in 2+ years.
2	hos	number or proportion of persons with a hospital episode in past year.
3	hltfp	number or proportion of persons with health status fair or poor.
4	jan	number or proportion of persons born in January.
5	mar	number or proportion of persons born in March.
6	may	number or proportion of persons born in May.
7	tdv	number or mean of doctor visits.
8	rad	number or mean of restricted activity days.
9	aic	number or mean of acute incidence conditions.
10	hei	number or mean of hopital episodes in past year.
11	hed	number or mean of hospital days in past year.

Table 4 INFLUENCE OF DESIGN WEIGHTS ON THE COEFFICIENT OF VARIATION FOR A CHARACTERISTIC WHICH IS UNCORRELATED WITH THE NHIS DESIGN

CHARACTERISTICS - PERCENTAGE OF PERSONS BORN IN A GIVEN MONTH FOR 11 MONTHS

NHIS SUPPLEMENT - ONE SAMPLE ADULT PER HOUSEHOLD

SUBDOMAIN AGE	RACE	SEX	HISPANIC	SAMPLE SIZE	MEAN WGTD CV	MEAN UNWGTD CV	MEAN RATIO CV's
ALL	.	.	.	44123	1.8	1.6	1.13
.	.	M	.	18335	2.8	2.5	1.12
.	.	F	.	25788	2.4	2.1	1.16
.	W	.	.	36850	2.0	1.8	1.12
.	W	M	.	15661	3.0	2.7	1.11
.	W	F	.	21189	2.7	2.3	1.14
.	B	.	.	6195	5.2	4.3	1.23
.	B	M	.	2191	8.6	7.1	1.21
.	B	F	.	4004	6.5	5.3	1.23
.	O	.	.	1078	12.4	10.2	1.22
.	O	M	.	483	18.5	15.2	1.22
.	O	F	.	595	16.9	13.7	1.23
.	.	.	HISP	2926	6.9	6.1	1.12
.	.	M	HISP	1218	10.5	9.4	1.12
.	.	F	HISP	1708	9.2	8.1	1.14
18-64	.	.	.	35610	2.0	1.8	1.14
18-64	.	M	.	15340	3.0	2.7	1.13
18-64	.	F	.	20270	2.7	2.4	1.15
18-64	W	.	.	29386	2.2	1.9	1.12
18-64	W	M	.	13055	3.2	2.9	1.11
18-64	W	F	.	16331	3.0	2.6	1.13
18-64	B	.	.	5221	5.7	4.6	1.23
18-64	B	M	.	1830	9.3	7.7	1.21
18-64	B	F	.	3391	7.0	5.8	1.21
18-64	O	.	.	1003	12.8	10.5	1.22
18-64	O	M	.	455	19.0	15.5	1.22
18-64	O	F	.	548	17.3	14.4	1.21
65+	.	.	.	8513	4.2	3.7	1.14
65+	.	M	.	2995	6.8	6.1	1.12
65+	.	F	.	5518	5.2	4.5	1.16
65+	W	.	.	7464	4.4	3.9	1.13
65+	W	M	.	2606	7.2	6.6	1.10
65+	W	F	.	4858	5.4	4.8	1.14
65+	B	.	.	974	12.8	10.6	1.20
65+	B	M	.	361	20.6	17.1	1.21
65+	B	F	.	613	16.1	13.4	1.20
65+	O	.	.	75	52.6	45.8	1.18
65+	O	M	.	28	74.7	72.3	1.04
65+	O	F	.	47	64.9	55.1	1.20

Figure 1, 2, and 3:
Comparisons of estimates of Standard Errors for the NHIS using models (1), (2) and (3)
y–axis: □ SE(model(2)) / SE(model (1))
X SE(model(3)) / SE(model (1))
x–axis: Variable IDs (see text & table 2)
Figure 1: SE for estimated totals of Core
Figure 2: SE for estimated means of Core
Figure 3: SE for estimated means of Supplement

Figure 2

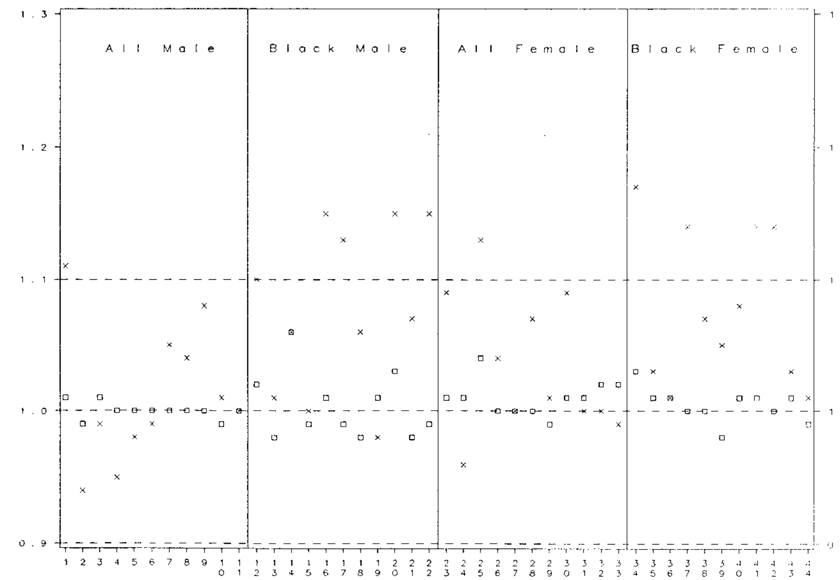

Figure 1

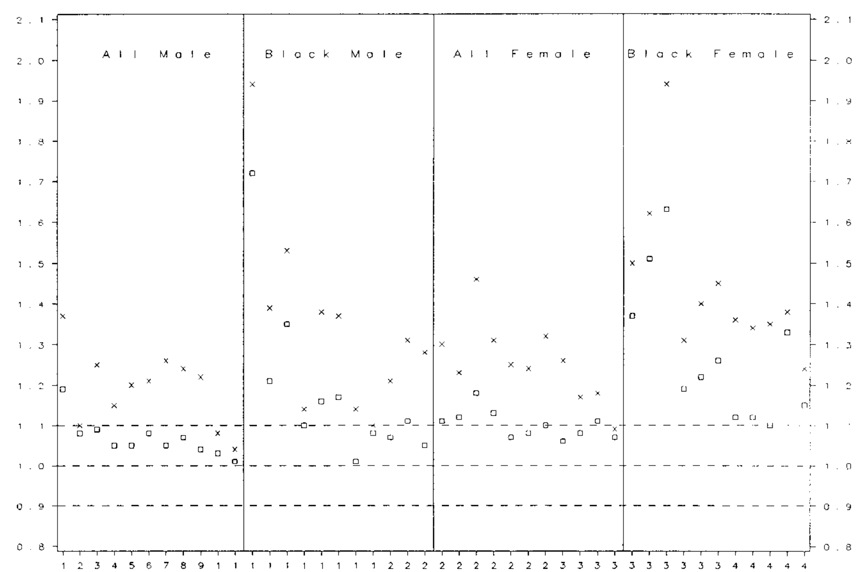

Figure 3

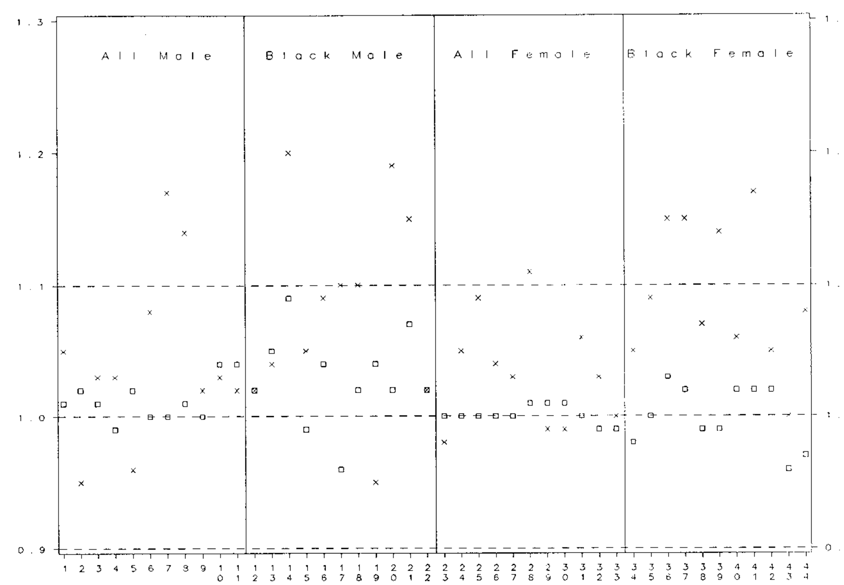

Figure 4 and 5:
Subseting NHIS data sets
Plotted SE(model(3)subsetted) / SE(model(1))
Figure4: SE for estimated means for Age 65+ Subset
Figure5: SE for estimated means for Black Subset

Figure4

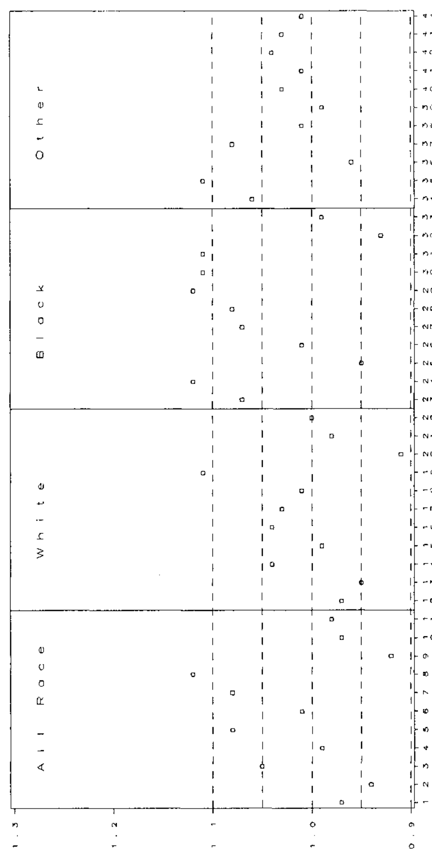

Figure5

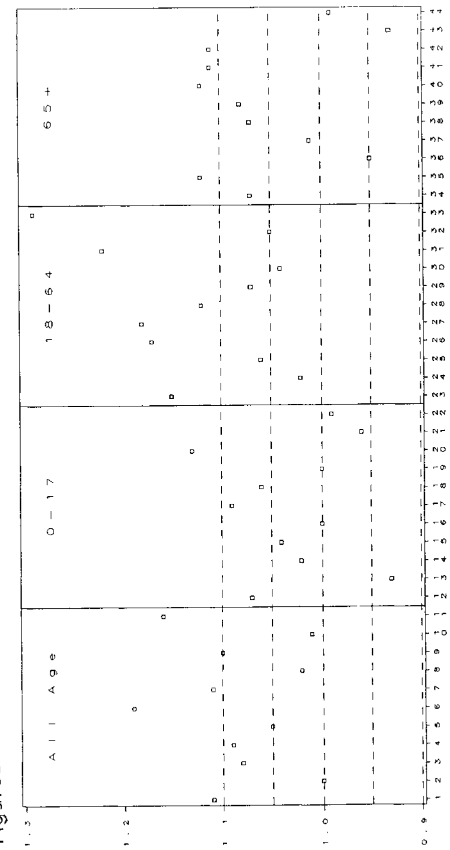

Table 5

EFFECT OF TRUNCATION ON THE NHIS CORE SAMPLE WEIGHTS

TRUNCATED WEIGHT = MINIMUM (ORIGINAL WEIGHT, 99th PERCENTILE WEIGHT)

SUBDOMAIN	SAMPLE SIZE (1000s)	PERCENT 1/ (STDERR) DR2Y	INFLUENCE 2/ MEASURES (1)	(2)	(3)	PERCENT (STDERR) HLTFP	INFLUENCE MEASURES (1)	(2)	(3)	PERCENT (STDERR) HOS	INFLUENCE MEASURES (1)	(2)	(3)	MEAN (STDERR) TDV	INFLUENCE MEASURES (1)	(2)	(3)
ALL	122.9	14.4 (0.17)	*	0.95	5	10.0 (0.13)	*	0.95	5	8.4 (0.09)	*	0.95	5	5.4 (0.06)	*	**	2
F	64.4	10.7 (0.17)	*	0.95	5	10.9 (0.15)	*	**	4	9.7 (0.13)	*	**	4	6.2 (0.09)	*	0.95	5
BLACK	19.6	15.0 (0.56)	*	0.91	9	14.7 (0.38)	*	**	1	8.8 (0.22)	*	**	0	4.8 (0.18)	*	0.94	6
NON BL,WH	3.6	19.4 (0.98)	*	**	2	8.2 (0.66)	0.96	0.87	14	6.5 (0.46)	1.02	0.92	8	3.9 (0.23)	*	**	1
NBW F	1.9	14.8 (1.13)	1.02	0.90	10	9.5 (0.84)	0.96	0.87	14	7.4 (0.68)	1.03	0.94	6	4.1 (0.34)	0.97	0.90	10
HISPAN	9.5	19.6 (0.62)	*	**	1	9.4 (0.45)	*	**	0	7.3 (0.29)	*	**	1	4.2 (0.16)	*	**	1
F HISP	4.9	14.5 (0.68)	*	**	2	10.9 (0.57)	*	**	0	9.4 (0.44)	*	**	0	4.9 (0.23)	*	**	1
18-64	73.7	17.2 (0.20)	*	0.95	5	9.3 (0.15)	*	0.95	5	8.8 (0.12)	*	0.94	6	5.3 (0.08)	*	**	4
18-64 F	39.0	11.3 (0.19)	*	0.95	5	10.2 (0.19)	*	0.95	5	10.9 (0.18)	*	0.94	6	6.4 (0.12)	*	0.92	8
18-64 WH	60.4	17.0 (0.21)	*	**	4	8.3 (0.16)	*	0.95	5	8.6 (0.13)	*	**	4	5.3 (0.09)	*	0.95	5
18-64 WH F	31.3	11.1 (0.20)	*	0.95	5	9.0 (0.20)	*	0.95	5	10.6 (0.19)	*	**	4	6.5 (0.13)	*	0.91	9
18-64 BL	10.9	17.0 (0.59)	*	0.93	7	17.2 (0.49)	*	**	1	10.8 (0.33)	*	**	2	5.4 (0.23)	*	**	3
18-64 BL F	6.4	11.2 (0.67)	*	0.85	15	18.7 (0.61)	*	**	0	13.1 (0.49)	*	**	2	6.2 (0.30)	*	**	3
18-64 NBW	2.3	23.2 (1.06)	*	**	2	8.6 (0.67)	*	**	2	6.9 (0.58)	1.02	**	5	4.1 (0.32)	0.98	0.95	5
18-64 NBW F	1.2	16.6 (1.32)	1.02	0.91	9	9.9 (0.85)	0.97	0.95	6	8.6 (0.87)	1.03	**	5	4.6 (0.48)	0.95	0.82	18
65+	14.6	10.5 (0.28)	*	**	2	30.5 (0.47)	*	**	4	17.0 (0.33)	*	**	2	8.9 (0.22)	*	**	2
65+ F	8.6	9.5 (0.33)	*	0.95	5	30.0 (0.55)	*	**	3	15.3 (0.41)	*	**	3	9.2 (0.30)	*	**	0
65+ WH	12.7	10.3 (0.29)	*	**	3	29.1 (0.48)	*	**	1	16.9 (0.35)	*	**	1	8.9 (0.23)	*	**	3
65+ WH F	7.5	9.5 (0.35)	*	0.95	5	28.5 (0.56)	*	**	1	15.2 (0.44)	*	**	2	9.1 (0.30)	*	**	1
65+ BL	1.7	11.6 (0.93)	0.98	0.91	9	45.9 (1.62)	*	**	2	18.0 (1.00)	*	**	2	9.3 (1.02)	*	**	1
65+ BL F	1.0	9.8 (1.00)	*	**	4	46.6 (1.76)	*	**	2	17.2 (1.33)	*	**	3	10.3 (1.56)	*	**	1

1/ computed using original weights 2/ influence measures
(1) percent-truncated weights / percent-original weights
(2) stderr-truncated weights / stderr-original weights
(3) combined change of percent and stderr:

* change of 1% or less
** change of less than 5%