STATE ESTIMATES FOR THE NATIONAL HEALTH INTERVIEW SURVEY USING A RANDOM DIGIT DIALING SUPPLEMENT

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Introduction.

The National Health Interview Survey (NHIS) collects a variety of information on the health, health practices and health care on individuals in the civilian, non-institutional population of the United States. For more information on the current NHIS design, see Massey, et al. (1989). Estimates from this survey are made for the nation and for selected demographic groups. Even so, there is still a demand for similar information at subnational levels, such as states. This is because health characteristics can vary geographically. Another related reason is that health programs may take place at subnational levels and statistics are needed at these levels to assess these programs. Although there are a number of types of subnational areas for which health information is desired, estimates at the state level are often needed and are even attainable for certain states. In this work, an emphasis is place on producing estimates for all fifty states and the District of Columbia.

The NHIS actually consists of a family of surveys, but the focus here will be upon what is called the NHIS supplemental survey which samples one adult per sampled household and collects information on topics of current interest. In the design for 1995-2004 it is anticipated that 30,000-40,000 adults will be sampled. In this paper a reference to NHIS will refer to this supplemental survey.

In Figure 1, each state's expected adult sample size is plotted against the adult population size. States with NHIS sample sizes of 1000 or more could provide reliable stand-alone NHIS estimators for several domains of interest. As can be seen, alternative methods are needed to provide estimates for all states and D.C. Sirken and Marker (1993) have evaluated the potential for providing state estimates from the NHIS by supplementing the NHIS with a sample from a telephone frame and indicate that telephone supplementation is feasible in many states. The main limitation is the size of the non-telephone population. In Figure 2, the percent of state households in 1990 without telephones is plotted against expected state sample size. It can be seen that telephone coverage, within a state, ranges from about two to thirteen percent, with a median of about 5 percent.

State estimation for the NHIS via a dual frame survey (NHIS and RDD supplementation) is being considered by the National Center for Health Statistics (NCHS). In fact the 1995/2004 NHIS redesign will use states as the primary stratification variable. This feature will allow one to, more easily, supplement the NHIS with an RDD survey.

The NHIS sample of PSUs is drawn once and used for a ten year period. Only the RDD sample design is under the sample designer's control. In this work, we use the identity of the NHIS sampled PSUs to determine the optimal allocation of the RDD sample (the optimal allocation is the allocation that produces the minimum variance for a selected estimator and specific population). This paper compares this optimal strategy with two other strategies that are sub-optimal but easier to implement.

Dual Frame Design Considerations

Many state RDD surveys in operation have sample sizes usually in the range of 1000 - 2000 persons and are designed to stand alone. In this paper, a sample of 1000 telephone households will be selected from each state and exactly one adult will be sampled per household. Furthermore, it is assumed that a state's telephone frame can be partitioned by distinct sampled and non-sampled NHIS PSUs. Implementation costs will not be considered.

Three RDD sampling designs

Design 1 (Independent RDD): This RDD sample is a simple random sample (SRS) of 1000 telephone households within the state and is independent of the NHIS sample. This method is considered the standard.

Design 2 (Stratified RDD): Each state is first stratified by universe state PSUs, and then the RDD sample size of 1000 is allocated proportionately by PSU size. Sampling is SRS within a PSU, and the RDD sample is independent of the NHIS sample.

For suitable unbiased estimators, this sample allocation is optimal for a stand-alone RDD survey if the variance within each PSU is proportional to the inverse of the RDD sample size.

<u>Design 3</u> (Dependent RDD): The state will be stratified and sampled similarly as in design 2, but the sampling rate will depend on the NHIS sampled PSUs. Specifically, the unsampled NHIS PSUs will be oversampled with the RDD sample while the sampled NHIS PSUs will be undersampled. Details on the derivation of the optimal allocation will be presented elsewhere.

Since the optimal sampling rate depends on population parameters, an approximate, realizable, suboptimal sampling rate is implemented that only depends on the population size of the PSUs. This sampling rate is optimal for a combined RDD and NHIS sample if all variances within each PSU are proportional to the inverse of the effective RDD plus NHIS sample sizes.

Designs 1, 2 and 3 are listed in ascending order by costs and implementation difficulty, but this order also suggests improved precision. The level of improved precision will dictate whether a more costly option is justified.

<u>Dual Frame Estimators Under Consideration</u>

In this preliminary work the target state characteristic is a proportion, R, and the goal is to determine the degree to which designs 2 and 3 provide superior precision in estimation over the standard design 1.

Since estimated ratios do not usually have variances which can be expressed in mathematically tractable forms, all estimators will be linearized as follows:

Define $\hat{R}=\hat{Y}/\hat{Z}$ to be an estimator for a population ratio: $R=Y/Z$. The linearized form will be

$$\hat{X}=(\hat{Y}-R\cdot\hat{Z})/E(\hat{Z}), \quad R=E(\hat{Y})/E(\hat{Z})$$

Variances based on this linearization will be used to determine optimal allocations. We will restrict estimates of Y and Z to be unbiased, linear combinations of Horvitz-Thompson estimators, see Cochran (1977).

Three estimators corresponding to RDD sampling designs 1, 2 and 3 are denoted by $\hat{R}_H,\ \hat{R}_I,\ \text{and}\ \hat{R}_D$ and respectively and their linearized forms, $r_H,\ r_I,\ \text{and}\ r_D$ are defined below.

For design 1:

$$\hat{R}_H=\frac{\hat{Y}_{(fNT)}+\lambda\hat{Y}_{(fT)}+(1-\lambda)\,\hat{Y}_{(RDD)}}{\hat{Z}_{(fNT)}+\lambda\hat{Z}_{(fT)}+(1-\lambda)\,\hat{Z}_{(RDD)}}.$$

Its linearized form is:

$$r_H=\hat{X}_{(fNT)}+\lambda\hat{X}_{(fT)}+(1-\lambda)\,\hat{X}_{(RDD)},$$

where

$$\hat{X}_{(fNt)}=(\hat{Y}_{(fNt)}-R\cdot\hat{Z}_{(fNt)})/Z$$

is the face-to-face estimator for the non-telephone domain,

$\hat{X}_{(ft)}$ is the corresponding face-to-face estimator for the telephone domain, and

$\hat{X}_{(RDD)}$ is the corresponding RDD estimator for the Telephone domain.

Here, $0\le\lambda\le1$, and λ is optimally assigned a value to minimize $\mathrm{Var}(r_H)$. This optimal λ is a function of the variances of the component NHIS and RDD estimators which are in general unknown. A practical λ defined as follows can be used:

if n_f = effective sample size for the Telephone domain for the NHIS, and
n_{rdd} = effective sample size for the RDD survey

$\lambda = n_f / (n_f + n_{rdd})$.

This λ is usually the reduction of the optimal λ whenever suitable regularity conditions are imposed.

For estimators r_I and r_D the above definitions are still used, but now defined at the PSU level.

For design 2:

$$r_I=\hat{X}_{(fNT)}+\sum_i(\lambda_i\hat{X}_{(fT)\,i}+(1-\lambda_i)\,\hat{X}_{(RDD)\,i})$$

Here, $\hat{X}_{(fNT)}$ is defined as in design 1, but now

$$\hat{X}_{(ft)\,i}=(\hat{Y}_{(ft)\,i}-R\cdot\hat{Z}_{(ft)\,i})/Z$$

with $\hat{X}_{(RDDi)}$ being analogously defined.

Note $0\le\lambda_i\le1$, and $\lambda_i = 0$ if PSU is not in the NHIS sample.

If PSU i is in sample, a similar definition of λ_i to that for Design 1 is used, but now at the PSU level.

For design 3:

The estimator, r_D, is of the same functional form as r_I, but λ_i is a function of the NHIS-dependent allocation RDD allocation.

It should be noted that r_I and r_D are conditionally unbiased for characteristics restricted to telephone domains. Thus, the unconditional variance of r_I and r_D will have no between-PSU variation on the telephone domain.

Now, many states have stand-alone RDD surveys. The additional burden of the dual frame may not lead to any substantial improvement over a stand-alone RDD estimator. For this reason a stand-alone estimator, r_R, is also considered. This estimator will be biased, and this bias must be considered in any comparisons with r_H,r_I, and r_D.

Implementation and Evaluation of Estimators

Theoretical Evaluation of Estimators

In design 3, the RDD allocation is defined conditionally given the NHIS sampled PSU's, and it will be optimal under suitable population conditions. Under these conditions, r_D will have smallest variance among r_D, r_I and r_H. In reality, only limited information is available on the true population. Thus, to evaluate relative performance among the three estimators, a pseudo U.S. population was created, along with key features of NHIS and RDD sampling components, to allow the computation of theoretical sampling variances for each of the three estimators. The generated population and NHIS and RDD sampling designs had the following characteristics:

Simulated Population Characteristics

1. The U.S. population was defined at the universe PSU level, and stratified within state by the actual NHIS PSU strata. The population defined by the 1990 U.S. Census was used as a substitute for the NHIS reference population. Using 1990 U.S. Census counts of county population by age, race and ethnicity, PSU counts were determined. Using the U.S. Census sample, the percent of occupied households with a telephone was used to estimate the percent of occupied households with a telephone in each PSU.

2. Black and Hispanic subdomains were targeted for oversampling in the NHIS. The actual methodology would require U.S. Census block information which was not available for this study. To capture the essentials of within-PSU sampling, it was assumed that each PSU was substratified into at most three race/ethnicity strata-Non-Hispanic Blacks, Hispanics and Others. It was assumed that the telephone coverage at the PSU level was uniform across these substrata.

3. No true health characteristics were available for the entire universe, but a characteristic to emulate smoking status by telephone status was generated. In Thornberry (1987) it was observed that in the U.S. 30% of adults in telephone households smoked while 50% of adults in non-telephone households smoked. These rates were used to simulate a population of smokers and nonsmokers. Within each PSU and race/ethnicity stratum the population proportion who smoked was generated by a logistic probability model. Overall, the rates were generated so that $E(p) = .3$ and .5 for the respective telephone and non-telephone domains. The proportions were generated independently over the PSU's.

4. Within-PSU NHIS sampling was generated as follows. The total PSU population counts obtained for Hispanics, non-Hispanic Blacks, and Others (non-Black and Non-Hispanic) were used to determine expected within PSU sample sizes. These expected counts were derived using specifications in the 1995 NHIS redesign report (Westat (1994)) where U.S. Census blocks were partitioned into substrata within a PSU based on the composition of race/ethnicity within the block.

As mentioned above, census block data were not used here. Instead, the census PSU population by race/ethnicity was allocated to the PSU substrata based on the average demographic composition of the substrata nationally. Using the national average household size for the three race/ethnicity groups and Westat's recommended sampling and screening rate within each substrata, expected sample sizes were obtained.

5. Within-PSU NHIS sampling variances were hypothesized for each PSU using the characteristics of element 3.) and the samples sizes of element 4.) above.

6. Durbin (1967) probabilities of PSU selection were used within the state strata.

7. The sampling moments of the statistics r_D and r_I were computed conditionally for each possible NHIS sample of PSUs then the expectations were taken over

all possible NHIS samples of PSUs. The RDD allocation was conditional for Design 3), and the definition of λ was a function of the sampled NHIS PSUs. Except for Texas, North Carolina and Georgia, the total number of possible PSU samples is computationally manageable on a SUN workstation. The moments of r_H, r_R were computed by direct calculation.

Evaluation of Estimators and Designs

Using the pseudo U.S. population and the NHIS and RDD generated designs, the coefficients of variation (CV) for each of r_H, r_I, and r_D were computed along with the root relative mean-squared error (RRMSE) of r_R. An analysis of the four estimators with respect to CV and RRMSE suggests that performance of estimators is related to NHIS design characteristics - percent of State population in Nonself-representing strata (NSR) and size of NHIS State sample.

In Figure 3 the NHIS states have been partitioned into four groups defined by NSR percent and NHIS sample size (see Table 1 for specifications). Table 1 provides the relative performance of r_D, r_I and r_R to r_H.

On examination one sees that for states with small NHIS sample sizes and large NSR populations, e.g., Arkansas, the biased RDD estimator is on the average superior to the others with respect to relative mean-squared error. In these states there may be insufficient non-telephone households to allow a sufficiently precise r_H, r_D, or r_I estimator to overcome the bias component of r_R. In these states one might consider alternatives to unbiased estimators.

In states with small NSR populations, the NHIS sample is for the most part in self-representing areas. In these cases the RDD sampling methodology of Designs 1, 2, and 3 lead to similar RDD allocations. If the state has a large NHIS sample, e.g., Massachusetts or California, methodologies for r_D or r_I may be slightly better than r_H, but r_D may be only marginally better than r_I. If the state has a small NHIS sample, e.g., Rhode Island, it appears that any advantage of r_D or r_I over r_H is marginal, and would probably not be worth the additional expense.

Now, the states in which Design 3 and estimator r_D are superior are those with large NHIS samples and large NSR populations, e.g., Virginia. Here, both r_D and r_I eliminate much of the NHIS variance component of between-PSU variance on the telephone domain, but RDD sampling Design 3 avoids sampling state PSUs already having a large NHIS sample. The average relative accuracy of r_D to r_I was .83, which seems substantial.

A summary of the practical comparisons in is in Table 2.

Future Work

There is often an interest in obtaining subpopulation estimates within a State. It is planned to evaluate dual-frame dependent sample designs for select subpopulations. Also, an examination of the ability of a single dependent design to provide good estimates for a variety of population characteristics is planned.

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Figure 1: Expected State NHIS Sample vs Adult Population

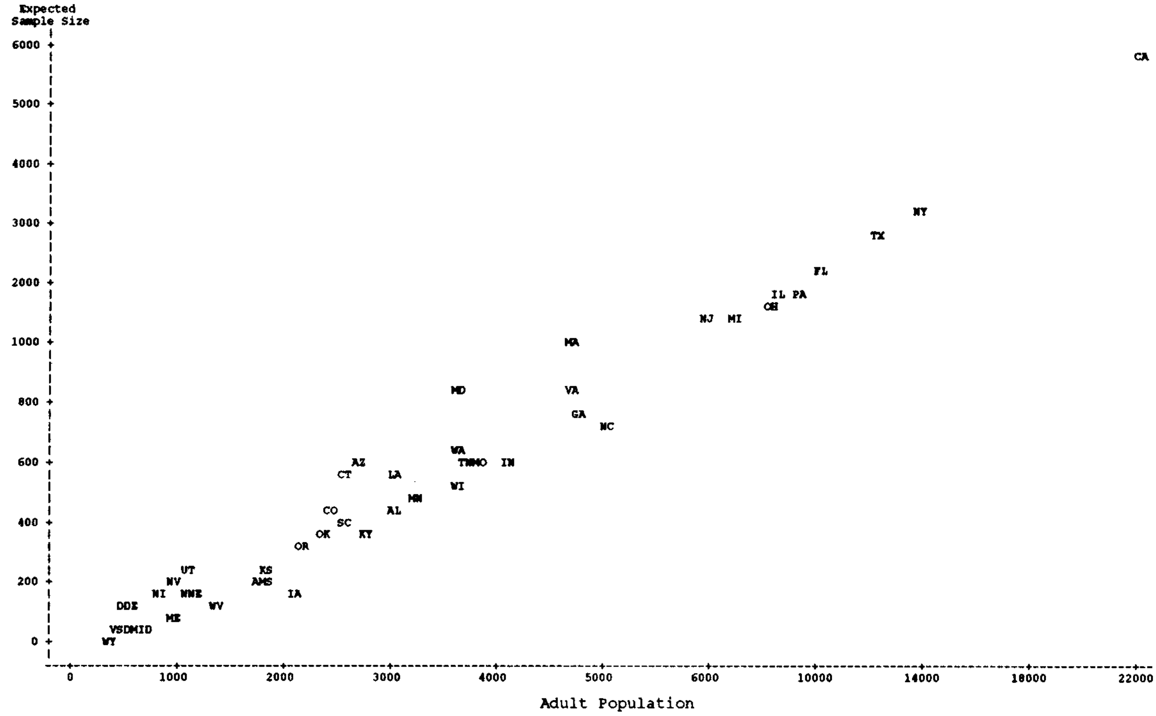

Figure 2: Percent of State Households Without Telephones vs Expected NHIS State Sample Size

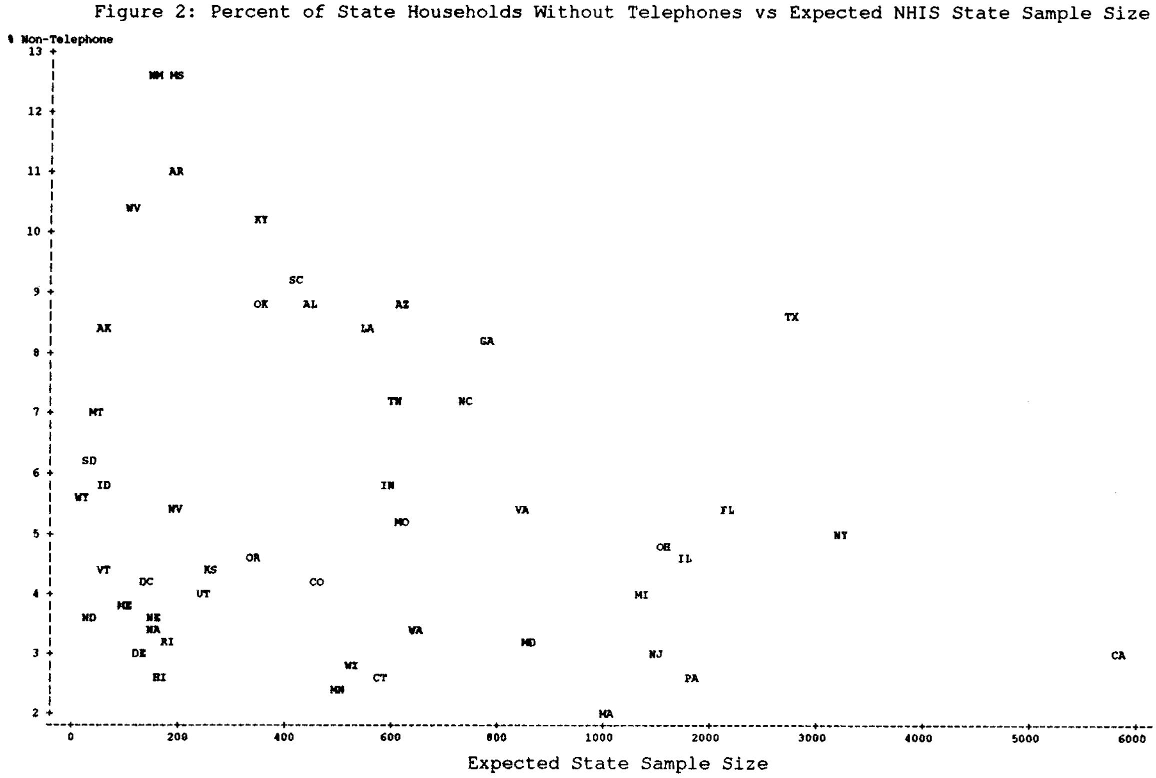

Figure 3: States Grouped by NHIS
Percent Non-self-representing (NSR) Areas vs Expected Sample Size

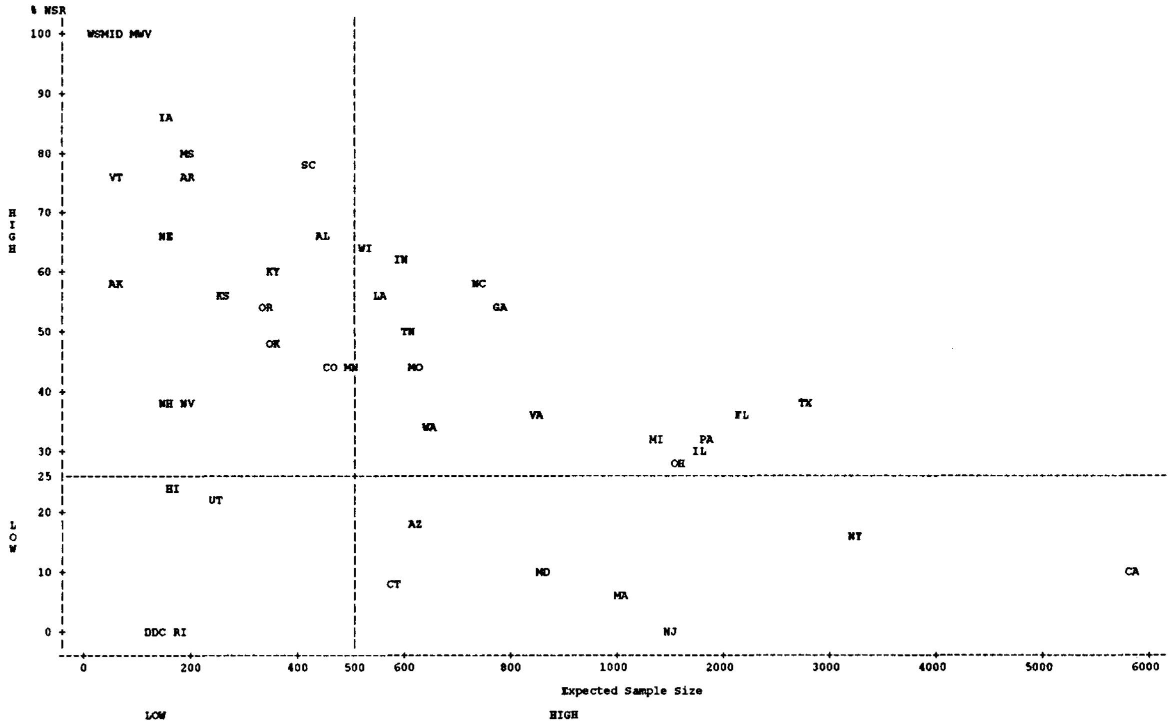

Table 1: Comparisons of Dual Frame State Estimators
Relative precision averaged over states with the specified characteristics:

High NSR - Percent of sample in NSR $\geq$ 25%
Low NSR - Percent of sample in NSR < 25%

High Sample - State sample size $\geq$ 500
Low sample - State sample size <500

Average relative accuracy: $CV(r_D)$ to $CV(r_H)$

		NHIS Sample Size Low	High
NSR Population	High	.95	.83
	Low	.99	.95

Average relative accuracy: $CV(r_I)$ to $CV(r_H)$

		NHIS Sample Size Low	High
NSR Population	High	.95	.86
	Low	.99	.97

Table 1: (continued)

Average relative accuracy: $RRMSE(r_R)^{1/2}$ to $CV(r_H)$

		NHIS Sample Size Low	High
NSR Population	High	.80	1.22
	Low	1.02	1.61

Table 2: Summary of Practical Comparisons

Recommended Estimators/Designs:

		NHIS Sample Size Low	High
NSR Population	High	Design 1 r_R	Design 3 r_D
	Low	Design 1 r_H	Design 2 r_I