DESIGN EFFECT VARIATION IN THE NATIONAL MEDICAL CARE EXPENDITURE SURVEY

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Introduction

Data from complex survey designs require special consideration with regard to variance estimation, due to the departure from simple random sampling assumptions. Design components often include unequal selection probabilities of elements in the population, with several stages of clustering. Stratification and proportionate representation are two widely used design features of many general purpose surveys to increase precision and minimize bias. Disproportionate sampling is another strategy adopted to insure sufficient representation of specific subgroups from an underlying population, while simultaneously allowing for the capacity to yield reliable estimates of relevant characteristics for the complete target population. In addition, the estimation procedures often include unequal weighting factors, adjustments for nonresponse, and poststratification.

Standard methods of variance estimation which assume simple random sampling generally result in an under-estimation of variance, when used with data from a complex survey design. Observations made on sampling units are not independent due to the correlations induced by cluster sampling and stratification. Several methods of variance estimation have been developed, which incorporate the complex survey design components in their derivation. In this study, design effects are determined for a representative set of survey statistics specific to data from the National Medical Care Expenditure Survey. The survey statistics under consideration estimate medical care utilization, expenditures, and health insurance coverage characteristics of the U.S. population. These statistics are expressed in terms of domain means, and proportions. Controlling for criterion variable type and range, class of statistic and sample size, the design effect variation is examined. In addition, the accuracy of alternative methods of variance estimation appropriate for complex survey data, which include the average design effect model and relative variance curve technique, are compared.

Design of the National Medical Care Expenditure Survey

The National Medical Care Expenditure Survey (NMCES) has been established to assess the health insurance coverage, health-related utilization, costs and sources of payment for the civilian population of the United States from a multistage national probability sample of approximately 14,000 households. The data are meeting the needs of government agencies, legislative bodies, and health professionals for more comprehensive national data required for the analysis and formulation of national health policies. The survey was designed to provide data for a major research effort in the Division of Intramural Research of the National Center for Health Services Research (NCHSR) and cosponsored with the National Center for Health Statistics (NCHS). The survey was conducted from samples chosen by two survey organizations, the Research Triangle Institute (RTI) and the National Opinion Research Center (NORC). Data collection was applied to the same panel of sample households in three rounds of personal interviewing and three rounds of telephone interviewing to cover the year 1977.

The sampling design can be characterized as two independent replicates of similar four stage probability samples of the noninstitutionalized population, with multivariate stratification in the first two stages (Cohen and Kalsbeek, 1981). The survey population for NMCES included both residential housing units and a special class of group quarters. Sampling units in the first three stages of each replicate are land areas ranging in size from small groups of contiguous counties in the first stage to small area segments consisting of a few dozen housing units. Sampling units in the first stage were generally stratified by location in the country, degree of urbanization, and size of city (RTI) or by family income and percentage black (NORC). Selection in each of the first three stages was with probabilities proportional to certain size measures. Individual housing units were chosen in the fourth stage from a machine-readable frame by a systematic sampling method.

Estimation from NMCES implies the need for appropriately formulated sampling weights to reflect the variation in selection probablities for observation units. NMCES sampling weights consist of the reciprocal of the original selection probability, multiplied by a number of needed adjustments. A nonresponse adjustment was used to partially accommodate the effect of nonresponse among eligible units, which for one reason or another, did not participate initially or for all rounds of interviewing. A second adjustment was designed to accommodate the smoothing of excessively large sampling weights. A third so-called post-stratification adjustment served to force sums of weights to presumably more accurate Census population figures for the nation by age, race, and sex.

Design Effect Variation in the NMCES

Given the complex nature of the NMCES survey design, the assumptions of independence and equal selection probabilities are not satisfied. The extent of the departure from simple random sampling assumptions, and its impact on variance estimation, is measured by the design effect. The design effect is defined as the ratio of the true variance of a statistic to the variance derived under simple random sampling assumptions. The more notable the deviation from unity, the more severe the risk of inaccurate statistical inference when estimating variances for statistics derived from complex survey data under simple random sampling assumptions.

The impact of a complex survey design on variance estimation is best illustrated by the following relationship:

$$\sigma^2_{\text{complex}} = \sigma^2_{\text{SRS}} \left[1 + \rho\,(\bar{n} - 1)\right]$$

where $\sigma^2_{complex}$ is the true variance of a statistic derived from complex survey data,

σ^2_{SRS} is the variance estimate obtained for the statistic under simple random sampling assumptions,

$\bar{n}$ is the average cluster size, and

ρ is the intra cluster correlation coefficient.

Consequently, the design effect can be expressed as: Design Effect =

$$\frac{\sigma^2_{complex}}{\sigma^2_{SRS}} = [1 + \rho (\bar{n} - 1)] .$$

When the effects of clustering are dominant in a survey design, and the average cluster size is moderate to large, the design effect markedly deviates from unity. It presents a powerful argument for the need to appropriately accommodate the complexities of a survey design in variance estimation strategies and subsequent analyses.

The three most generally accepted and frequently used techniques are the method of Balanced Repeated Replication (BRR), the "jackknife" method, and the Taylor series linearization method (McCarthy, 1966; Kish and Frankel, 1974). These variance estimation strategies have been incorporated in several of the prominent statistical packages. Use of these procedures would be prohibitive with respect to computation time and cost, however, if applied to each parameter estimate of interest. Consequently, most users are willing to accept modest levels of bias that result when alternative cost-effective variance estimation strategies are applied. Two alternative variance estimation procedures which incorporate the complexities of the survey design in their derivation have gained widespread usage in the statistical community. They are referred to as the average design effect model and the relative variance curve technique (Cohen, 1981, 1982).

Using data from the NMCES, the accuracy of these alternative methods of variance estimation were compared for a representative set of statistics expressed in terms of population totals and means (Cohen, 1982). Three distinct classes of statistics were considered in an attempt to represent the diverse set of statistics available from the NMCES data base: narrow, medium and wide range. The average design effect model consistently demonstrated a superior performance in its capacity to yield variance estimates with the greatest accuracy.

This study will further investigate the properties of the average design effect model and determine whether gains in precision and accuracy are achieved through the introduction of stratification on the criterion variable of interest. For a wide range of survey statistics, the design effect variability will also be examined to determine those conditions under which stability and proximity to unity are noted. Similarly, conditions associated with marked design effect departures from unity will be identified. In this study, approximately unbiased estimates of variance for survey statistics are generated through the Taylor Series linearization method, and used in the determination of design effects (Woodruff, 1971).

To provide for a comprehensive investigation, design effects are determined for a representative set of survey statistics which estimate medical care utilization, expenditures, and health insurance coverage of the U.S. population. The utilization measures include the number of physician visits, hospital admissions and number of prescribed medicines. More specifically, physician visits consisted of all ambulatory physician contacts, excluding telephone calls. Hospital admissions included admissions of less than 24 hours and those for women giving birth. Newborns were not counted as separate admissions unless they were admitted separately following delivery. Prescribed medicines included any drug or other medical preparation prescribed by a physician, including refills. Expenditure data for each of these utilization measures were also considered: physician visit expenditures, total expenditures for prescribed medicines, and total expenditures for all hospital admissions (with charges excluded for inpatient physician services). The measure of health insurance coverage indicated the presence of private health insurance coverage. In addition, the domain defining demographic measures for the survey statistics under consideration included age (<5, 5-14,...55-64, 65+), race (white, nonwhite), sex (male, female), health status (excellent, good, fair, poor), marital status (<17, never married, married, widowed, separated, divorced), years of education (0-8, 9-11, 12, 13-15, 16+, under 17 years of age), employment status (worked, unemployed, not in labor force, <16) and size of city (SMSA, non-SMSA).

The diverse set of selected criterion variables also served to represent three distinct classes of survey statistics: narrow, medium and wide range. More specifically, the class of narrow range statistics was determined by data at the individual level, whose measurements generally fall within the range of 0-3. These measurements usually serve to indicate the presence or absence of a population attribute or its frequency of occurrence. Similarly, medium range statistics consist of measurement which infrequently fall outside the range of 0-10. Wide range statistics are characterized by data more continuous in nature that have much higher upper bounds.

The class of narrow range statistics is represented by NMCES data on insurance coverage, and number of hospital admissions. Data on ambulatory visits and number of prescribed medicines served to represent the medium range class. The class of wide range statistics is represented by the following measures: total expenditures for hospital admissions, physician expenditures, and total expenditures for prescribed medicines.

For each of the selected criterion variables, domain estimates were generated in terms of population means or proportions when

appropriate. The domain estimates are defined by marginal or cross-classified distributional categories of the selected demographic measures. For example, consider the mean annual expenditures for ambulatory physician visits within specific age-race-sex-health status classes of the U.S. population. The domain estimate, $\bar{Y}_g$, is derived as:

$$\bar{Y}_g = \frac{\sum_i W_i X_{gi} Y_i}{\sum_i W_i X_{gi}}$$

where Y_i is the ith individual's expenditures for medical provider visits,

W_i is the ith individual's sampling weight, expressed as the reciprocal of its selection probability and multiplied by nonresponse and post-stratification adjustments, and

X_{gi} = 1 if the individual is a member of the gth age-race-sex-health status domain,

= 0 otherwise.

Controlling for criterion variable type and range, class of statistic and sample size, the design effect variation is examined.

Tables A-G present the design effect variation for domain estimates of the selected criterion variables expressed in terms of population means or proportions. The quartile boundaries on sample size for the set of domain estimates under investigation were cross-classified by the tertile boundaries on the resultant mean (or proportional) estimates of the respective health care measures, yielding twelve distinct strata. Within each of these strata and their marginal classes, the average design effect, its standard error and the sample range of design effects were derived.

The most notable pattern in design effect variability was the positive incremental association of sample size with the value of the average design effect. This relationship was most obvious for domain estimates of the proportion of the population with private insurance coverage. In this setting, the average design effect ranged from 1.779 for domain estimates based on sample size less than 499, to 7.212 for sample sizes greater than 4960. Similarly, the pattern was quite evident for domain estimates of the mean number of prescribed medicines and mean expenditures for prescribed medicines. In the first setting, the average design effect differed significantly across stratum boundaries on sample size with a mean of 1.393 for domains characterized by $n \leq 498$, contrasted to a mean design effect of 2.525 for $n \geq 4961$. The pattern was also noticeable for domain estimates of the mean number of ambulatory physician contacts and related mean expenditures, though to a lesser degree. The pattern was least detectable for the domain estimates of the mean number of hospital admissions and related expenditures. Specifically, the average design effect for domain estimates of mean hospital expenditures differed significantly, with a mean of 1.07 for $n \leq 498$ compared to a mean design effect of 1.201 for $n \geq 4961$. All tests of statistical significance are performed at the .05 level and consider z tests based on the asymptotic normality of the average design effects for specified domains.

One potential explanation for this relationship on the insurance coverage data is the small range of variability exhibited by proportions as a function of the constraint: $0 \leq P(1-P) \leq .25$. Consequently, the effects of clustering are more pronounced. In addition, ultimate cluster units in the NMCES sample design are the household or family. Since a strong relationship exists between individuals in the same household with respect to their insurance coverage, a clustering effect induced by the survey design was noted in the estimated variance. A similar relationship is present for the number of prescribed medicines, ambulatory physician contacts and related expenditures among members of the same household. Hospital admissions, however, are rare events and least likely to be associated with a clustering effect induced by members of the ultimate cluster units. Consequently, domain estimates derived for this data base are characterized by rather stable design effects with small departures from unity.

No distinct relationship was observed between the average design effect and the respective tertile boundaries which characterized the distribution of criterion variable domain estimates. However, a significant incremental effect on the average design effect was noted in relation to the tertile distribution of domain estimates for insurance coverage. In this setting, the mean design effect was 2.532 for proportional estimates $\leq .7$, increasing to 3.458 for the proportionate range .701 - .761, and measured at 4.636 for proportional estimates in excess of .761. On occasion, the mean design effect was more pronounced for the middle class of the criterion variable distribution characterizing the domain estimates, though not constituting a statistically significant difference at the .05 level.

Comparison Between Average Design Effect and Relative Variance Curve Strategy

Variance estimates were not directly computed for each statistic considered in the NMCES, due to the constraints of computation time and cost. As noted, the two most frequently used alternative variance estimation strategies, appropriate for complex survey data, were the average design effect model and relative variance curve technique. Using NMCES data on health expenditures, utilization and health insurance coverage, the accuracy of these alternative methods of variance estimation were compared. Two design effect procedures were considered in the comparisons: the average design effect model stratified by sample size and criterion variable boundaries, and without stratification. For the design effect models, the variance of a domain estimate is derived by multiplying the respective variance estimated under simple random sampling assumptions with the appropriate design effect.

The relative variance curve technique makes use of the empirically determined relationship

between an aggregate statistic, expressed as a population total, Y, and its relative variance. The relationship is expressed as:

$$\text{Rel Var } (Y) = \frac{S^2_Y}{Y^2} \doteq \alpha + \frac{\beta}{Y}$$

where S^2_Y is the variance of the statistic generated from complex survey data, and α and β are model parameters.

Relative variances of ratio estimators, such as population means, are derived by considering the relationship which specifies the relative variance is approximately equivalent to the sum of the relative variance of the statistic's numerator and denominator components. The relationship is expressed as:

$$\text{Rel Var } (R) \doteq \text{Rel Var } (N) + \text{Rel Var } (D)$$

where $R = \frac{N}{D}$,

N is the numerator estimate, and D is the denominator estimate of the ratio estimator, R.

The relative variances of the numerator and denominator components are then estimated in the manner specified for aggregate totals. Consequently, the relative variance of the ratio estimator is estimated as:

$$\text{Rel Var } (R) \doteq \hat{\alpha}_N + \frac{\hat{\beta}_N}{N} + \hat{\alpha}_D + \frac{\hat{\beta}_D}{D}$$

As in the average design effect model, only a representative subset of related parameter estimates are considered in the determination of the prediction equation. It is advised that the subset of related statistics included in this curve fitting procedure are defined by domains whose underlying demographic characteristics insure a wide range of variability in parameter estimates. Variance estimates of these statistics are derived by one of the direct methods appropriate for complex survey data.

Several alternative curve fitting procedures with different optimization criteria have been considered for estimating model coefficients. These include a weighted least squares estimation strategy, and an iterative procedure that minimizes the relative squared deviations of predicted and observed relative variance estimators (Cohen, 1979). Once the model coefficients are determined, variances can be predicted for all related statistics by multiplying the resultant relative variance estimates by the square of the statistic.

To measure the accuracy of the respective variance estimation strategies, the average relative absolute difference between direct and predicted estimates of variance for domain specific population estimates, was considered. The measure took the form:

$$\bar{A} = \sum_{i=1}^{n} = \frac{\left|\hat{S}^2_{pi} - \hat{S}^2_{oi}\right|}{\hat{S}^2_{oi}}$$

where $\hat{S}^2_{oi}$ is the variance estimated by the Taylor Series linearization method for the i-th domain specific population estimate, S^2_{pi} is the variance predicted by either the average design effect or relative variance curve method for the i-th domain specific population estimate, and n is the number of domain estimates that constitute a representative subset for the criterion variable of interest.

Table H presents the comparisons in accuracy for the alternative variance estimation techniques. Study findings revealed a consistently lower average relative absolute difference, $(\bar{A})$, for both design effect methods over the relative variance curve technique. All observed improvements in accuracy were significant at the .01 level as determined by application of paired t-tests. The null hypothesis of interest was specified as: Ho: no difference in accuracy. The improvements in accuracy were most prominent for the prescribed medicine and physician related parameter estimates. In addition, the comparison across the two average design effect methods revealed significant improvements in accuracy were obtained through the introduction of stratification.

The order of magnitude observed in the accuracy measure for the relative variance curve strategy was disturbing. The technique has gained a degree of respectability as a consequence of its theoretical justification and widespread usage among a large statistical audience. Given the potential costs incurred by application of one of the direct methods of variance estimation appropriate for complex survey data, most users are willing to accept modest levels of bias that result when alternative cost-effective estimation strategies are applied. The consistent improvement in accuracy obtained by the design effect estimation strategy argues that greater scrutiny must be given to the relative variance curve strategy prior to a decision for adoption.

Table I presents the relative percent reduction in the average absolute relative difference obtained by using the design effect model over the relative variance curve strategy. This measure, I, which also indicates the relative percent improvement in accuracy, is expressed as:

$$I = 100 \cdot \frac{[\bar{A}(RV) - \bar{A}(Deff)]}{\bar{A}(RV)}$$

where $\bar{A}$ (RV) and $\bar{A}$ (Deff) are defined as the average relative absolute deviation in variance estimates for the respective relative variance curve and design effect strategies.

The design effect models consistently yielded a reduction in $\bar{A}$ over the relative variance curve technique. For the average design effect model with stratification, the minimum relative reduction in $\bar{A}$ was 65 percent. For over 50 percent of the specified comparisons, the reduction was greater than 92 percent, signifying a marked improvement in accuracy. When comparisons were directed towards the percent improvement in accuracy obtained by the design effect model, the stratified model was consistently judged superior.

The ratio of standard errors for the accuracy measures of the respective variance estimation models were also presented in Table I. For each of the data sets under investigation, none of

the observed ratios relative to the relative variance curve method exceeded .58. In addition, the ratio for the design effect model with stratification relative to the overall average design effect model was consistently less than one with stratification. Further, the investigation revealed the range of absolute relative differences between predicted and Taylor Series variance estimates were markedly narrower for the design effect model (Table J). Consequently, this strategy also demonstrated a superior performance in its capacity to yield variance estimates with the greatest precision. In this setting, precision was defined in terms of the range of relative absolute deviations between predicted and Taylor Series variance estimates for the diverse set of specified domains.

Summary

An examination of design effect variability was considered for a representative set of survey statistics which estimate medical care utilization, expenditures, and health insurance coverage for the U.S. population. Generally, design effect variability was a function of criterion variable type and sample size. Sample size was observed to be associated with a positive incremental effect on the value of the average design effect. Similarly, design effect variability was influenced by the effects of differential weights, and clustering at the household level that were mirrored in the criterion variable selection. Since a strong relationship existed between individuals in the same household with respect to their health insurance coverage, number of prescribed medicines, ambulatory physician visits and related expenditures, a noticeable clustering effect yielded relatively higher design effects. For data on hospital admissions, a relatively rare event, the criterion variable was less affected by a clustering effect generated by household members. Consequently, domain estimates derived for this measure were characterized by rather stable design effects with small departures from unity. No distinct relationship, however, was observed between the average design effect and the selected intervals on the distribution of criterion variable domain estimates.

This paper also considers a comparison of two alternative methods that have gained widespread usage in the statistical community. In this setting, the design effect model consistently yielded variance estimates that were superior in terms of accuracy and precision when compared with those derived by the relative variance curve strategy. Further gains in accuracy were achieved for the average design effect model with the introduction of stratification. The results demonstrate that the decision concerning the method for adoption should not be indiscriminate. Measures of accuracy and precision must be defined, and the behavior of both methods compared for a representative subset of sample data. The method of variance estimation which displays the most superior performance for the specified measures should then be selected.

Acknowledgements

The author wishes to thank Vicki Burt for her valuable assistance in the statistical analysis, and Sherry Montag for her skillful typing of this manuscript. The views expressed in this paper are those of the author and no official endorsement by the National Center for Health Services Research is intended or should be inferred.

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Note

Tables A-G were not presented in this paper due to space limitations. They may be obtained from the author by writing to: Dr. Steven B. Cohen, National Center for Health Services Research, Room 3-50, Park Bldg., 5600 Fishers Lane, Rockville, Maryland 20857.

Table H. Comparison for average relative absolute difference.

Class of Statistics	Number of specified domains	Average Relative Absolute Difference $\bar{A}$ (S.E.)			Paired t-tests		
	n	Design effect model with Stratification	Average design effect Model	Relative variance curve Model	1,3	2,3	1,2
		(1)	(2)	(3)			
Population Means							
Narrow Range							
1. Hospital Admissions	386	.075(.003)	.080(.003)	.623(.028)	-19.319	-19.077	-2.817
2. Private Insurance Coverage	386	.197(.008)	.354(.012)	.556(.021)	-15.982	-14.011	-11.130
Medium Range							
1. Physician Visits	386	.110(.005)	.126(.005)	1.706(.059)	-26.914	-26.645	-2.362
2. Prescribed Medicines	386	.110(.004)	.153(.006)	1.423(.053)	-24.973	-23.877	-8.558
Wide Range							
1. Hospital Expenditures	386	.093(.004)	.097(.004)	.411(.023)	-13.471	-13.240	-2.535
2. Physician Expenditures	386	.093(.004)	.112(.005)	1.221(.041)	-27.117	-26.624	-2.943
3. Prescribed Medicine Expenditures	386	.104(.004)	.147(.005)	1.388(.043)	-29.629	-28.380	-8.771

+All test statistics were significant at the .01 level, when testing the null hypothesis Ho: No difference in accuracy across models.

Table I. Percent relative reduction in average absolute relative difference and ratios of standard errors for accuracy measures.

Class of statistics	Number of specified domains	Percent relative reduction in $\bar{A}$			Ratio of standards errors		
	n	1/3,	2/3,	1/2	SE(1)/SE(3)	SE(2)/SE(3)	SE(1)/SE(2)
Population Means							
Narrow Range							
1. Hospital Admissions	386	88.0,	87.2	6.3	.106	.118	.894
2. Private Insurance Coverage	386	64.6,	36.3,	44.4	.390	.580	.672
Medium Range							
1. Physician Visits	386	93.6,	92.6,	12.7	.081	.081	.991
2. Prescribed Medicines	386	92.3,	89.2,	28.1	.083	.104	.791
Wide Range							
1. Hospital Expenditures	386	77.4	76.4,	4.1	.184	.194	.948
2. Physician Expenditures	386	92.4	90.8	17.0	.101	.116	.877
3. Prescribed Medicine Expenditures	386	92.5	89.4	29.3	.098	.123	.795

[1]Denotes average design effect model with stratification.
[2]Denotes average design effect model.
[3]Denotes relative variance curve.

Table J. Range in values of relative absolute difference in variance estimates between predicted and Taylor Series values.

Class of statistics	Number of specified domains	Range in values of relative absolute difference		
		Design effect model w/strat.	Design effect model	Relative variance curve model
		(lower, upper)	(lower, upper)	(lower, upper)
Population Means				
Narrow Range				
1. Hospital admissions	386	<.001,.325	<.001,.353	.002,2.767
2. Private insurance coverage	386	<.001,.885	.003, 1.166	<.001,2.562
Medium Range				
1. Physician Visits	386	<.001,.568	<.001,.645	.020,5.896
2. Prescribed medicines	386	<.001,.425	<.001,.520	<.001,4.448
Wide Range				
1. Hospital Expenditures	386	<.001,.446	<.001,.453	.001,2.281
2. Physician Expenditures	386	<.001,.661	<.001,.756	.006,3.859
3. Prescribed medicine Expenditures	386	<.001,.424	<.001,.524	.038,3.955