# Producing State Estimates with the Medical Expenditure Panel Survey - Household Component

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Agency for Healthcare Research and Quality Working Paper No. 05011

March 2005

Suggested citation: Sommers J. Producing State Estimates with the Medical Expenditure Panel Survey - Household Component. Agency for Healthcare Research and Quality Working Paper No. 05011, March 2005, http://gold.ahrq.gov.

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## ABSTRACT

In recent years, there has been a growing need for estimates of health care expenditures at the state level. The Medical Expenditure Panel Survey (MEPS), Household Component (HC) is a survey designed to collect information on and produce national and regional estimates of health care expenditures. However, while the sample design allows for some state estimates to be produced, there is no assurance that the quality of these estimates are adequate for use, since the original purpose of the survey did not include production of state estimates.

This paper describes the results of research using data from the MEPS - HC to produce a selected group of state level estimates for the 30 states with largest populations. Three methods of estimation are used. Each method is evaluated using standard measures and conclusions about the quality of these estimates along with recommendations are given.

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**by**

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## Background

An investigation of results produced from large scale federal household surveys, reveals few state estimates produced from these surveys. The exception is Current Population Survey (CPS) conducted by the Census Bureau and sponsored by the Bureau of Labor Statistics, which is the source of state income, poverty and health care uninsurance rate estimates (Census Bureau Website c). However, the state personal income and uninsurance rate estimates are multiple year averages produced from combining several years of data. (DeNavas-Walt et. al., 2003) County and state level estimates of income and poverty are produced using special small area estimation techniques using CPS and other data. State estimates are rare and design-based one year estimates do not seem to be routinely published. State level estimates are not routinely produced from other large scale federal household surveys including:

- The National Health Interview Survey (NHIS), sponsored by the Centers for Disease Control and Prevention's National Center for Health Statistics (NCHS) and conducted by the Census Bureau, (NCHS website and Botman, et. al., 2000)

- The Survey of Income and Program Participation (SIPP), conducted by the Census Bureau,(Census Bureau Website a and Kostanich and Dippo, 2002)

- The American Housing Survey (AHS), sponsored by the Department of Housing and Urban Development and conducted by the Census Bureau, (Census Bureau Website b and Census Bureau Website d ) and

- The Medical Expenditure Panel Survey - Household Component (MEPS-HC) sponsored by the Agency for Healthcare Research and Quality (AHRQ) (Medical Expenditure Panel Survey Website and Cohen, 2000).

A basic indication explaining why state level estimates are not produced with these surveys can be found in the estimates that are produced with the CPS data by the Census Bureau. Multi-year averages and small area estimation techniques are used when the reliability of the design based estimates is poor. Multi year averages increase sample sizes and thus lower errors. Small area estimation techniques use modeling and other complex and time intensive estimation methods to" borrow strength" from data outside the state or outside the survey to improve results with poor precision that are produced using design-based survey estimation techniques, such as, weighted means and totals. (Ghoush and Rao, 1994)

For the large national federal surveys, unbiased design based estimates for states are possible. An unbiased estimate of the state average for any variable is simply the weighted sum of the variable for all sample units within the state divided by the sum of the weights for the sample units within the state. (Cochran, 1977) There are two reasons, however why design-based estimates for individual states are generally of poor precision for the large national surveys. The first reason is that to meet population subdomain and for key survey estimates for specified proportions, the survey sample sizes are generally allocated on a national basis. For general population-based national surveys, survey budgets do not allow adequate sample size in each state to produce state estimates with acceptable precision. There is generally no focus on state estimates, thus no minimum state samples. Even for surveys with state level stratification as a design feature, such as, the NHIS, given that the top10 states have over half the population, the sample sizes for the remaining states can fall below an ideal sample size.

Aside from the possible lack of adequate sample sizes in states, the sample designs used in the surveys listed above also make it difficult to produce high quality design-based estimates for states. All the surveys have stratified multi stage cluster sample designs. This involves sampling of clusters, sets of counties. This limits the samples in each state, no matter how many persons are in the final sample, to a limited number of counties within each state. This is done because of the costs of personal household visits to collect the information if the sample of persons were spread widely and evenly across the entire country. This clustering of the sample can have a large impact on the sampling error. If the average values for the variables being estimated vary considerably across the clusters of counties, then the sampling error is effectively limited by the number of county clusters. For further detail on the variances of cluster samples, see Cochran, 1977.

**Need for State Estimates from the MEPS - HC**

In year 2004, the increase in costs of health insurance was above 10% (Kaiser Family Foundation, 2004). Further, large numbers of persons are without health coverage (DeNavas-Walt et. al., 2003). At the same time state budgets have been hard hit by loss of revenues and increasing health care costs from Medicaid spending. In 2003 Medicaid spending increased 8% over 2002 levels and was 21.4% of all State spending. As a result most States, reduced Medicaid benefits, reduced Medicaid eligibility and implemented prescription drug cost control programs for Medicaid. (National Association of State Budget Officers, 2003)

Given the variety of methods being implemented by the States to control Medicaid and other health costs and to increase persons with health insurance, it is of great interest for all States to know which efforts have succeeded and which have not. To assess these results one must have reliable data. Health care usage and costs at the state level must be analyzed to determine if costs are increasing over time and if more people are using health care. It would also be of use to know who is using care and what types. For instance, how much care do certain parts of the population use and what type, doctor visits, hospitals etc..

Because of these data needs, there is an emerging drive within the Department of Health and Human Services (DHHS) to examine the feasibility of producing State data from population based surveys and other sources. This paper examines the possibility of producing selected State estimates from one core DHHS data source.

## State Estimates with MEPS - HC Data

### The MEPS-HC

National estimates of health care expenditures are an important resource for health policy makers and health services researchers. The Medical Expenditure Panel Survey (MEPS) collects information regarding the use and payment for health care services from a nationally representative sample of the U.S. civilian noninstitutionalized population. In addition to the annual nationally representative expenditures estimates from MEPS, there is a growing need for estimates at the subnational level. While MEPS was designed to ensure reliable estimates at the national and regional level for individuals, families, and selected population subgroups, recent research has focused on the capacity for subnational estimates. A 2004 MEPS Statistical Brief (Machlin, et. al., 2004) provided estimates of health care expenses and uninsured rates for the U.S. community population under age 65 in 10 large metropolitan areas. This paper examines the capacity for producing expenditure estimates with acceptable precision at the state level using the MEPS.

The sample of households for the MEPS Household Component (MEPS-HC) is a subsample of households that responded to the prior year's National Health Interview Survey (NHIS) conducted by the National Center for Health Statistics, Centers for Disease Control and Prevention. The MEPS sample is drawn from approximately one-half of the primary sampling units (PSUs) in the NHIS. Oversampling of households with Hispanics and African Americans carries over from the NHIS to the MEPS sample design. In addition, in forming strata for selection of the first stage sampling units or PSUs in the NHIS, State was used as a stratification variable. This design feature carries over from the NHIS to MEPS - HC since the MEPS - HC uses approximately half of the NHIS PSU's. In this paper the MEPS – HC design is investigated with respect to its capacity to support reliable state level estimates for a selected number of states.

### Number of PSU's

The first issue one must address when trying to make State estimates from a survey with a cluster sample is the number of PSU's available to make the estimates for each state. If the between PSU variance is large compared with the within PSU variance, a very small number of PSU's means a large error, regardless of the number of final stage sampling units. (Cochran, 1977). For this reason we checked the PSU structure for the MEPS. We found that if we ranked states by total population that the 10 largest states each had either more than 6 PSU's and/or had a number of certainty PSU's that covered a large portion (60% or more) of the state population. For the second largest set of states, those with population ranks from 11 through 20, the states contained at least 4 PSU's and/or had a certainty PSU that covered a large portion of the state population. For the 21$^{st}$ through 30ith ranked states, the minimum number of PSU's was 3, but most had 4 or more non certainty PSU's and population coverage of the selected PSU's was limited. However, since there are enough PSU's to calculate an error for each of these states, this third set of states are also used in the analysis. Most of the remaining small states had either 1 or no PSU's and these were not included in the analysis.

Design-Based State Estimates

The first step of the research was to develop simple design-based estimates using the MEPS-HC design structure and data for the year 2002 for 6 types of expenditures: total (all types combined), dental visits, inpatient facility stays, office based visits, outpatient doctor visits and prescription drugs. This was done using the weights that were created by post stratification to national CPS values for cells defined by age, race, gender and martial status. For each type of expenditure, an estimate for each state was made for the percent of persons who had that expenditure, the mean for those who had an expenditure and the total expenditures. These estimates were created for each of the 30 largest states defined by total population . Relative standard error results were averaged for each type of estimate for 3 state groups, the 10 largest states, the second ten largest states and the third ten largest states. These are called groups 1,2 and 3 in order from the largest to smallest states. Results are shown in Table 1. Maximum relative standard errors in each group are also shown.

The standard errors for the estimates shown in tables in this report were produced using a set of 64 partially balanced half samples and the balanced repeated replication method. (Wolter,1985). This was done to take into account the post stratification done to the sampling weights. For variance estimation purposes, the weights were post stratified for each replicate. We found that use of Taylor Series methods for this first set of design-based estimates gave similar results. However, this was not true for results produced and discussed latter in this paper and shown in Tables 2 and 3.

**TABLE 1**
**Average and Maximum Relative Standard Errors by State Size Group for Typical Estimates: National Post Stratification: MEPS-HC, 2002**

| | | Conditional Mean Expenditures | | Percent of Persons with Expenditure | | Total Expenditures | |
|---|---|---|---|---|---|---|---|
| **Expenditure Type** | **Size Group** | **Mean Rse** | **Max Rse** | **Mean Rse** | **Max Rse** | **Mean Rse** | **Max Rse** |
| all types combined | 1 | 0.0989 | 0.1697 | 0.0226 | 0.0327 | 0.2159 | 0.3437 |
| all types combined | 2 | 0.1602 | 0.3223 | 0.0291 | 0.0424 | 0.3336 | 0.5232 |
| all types combined | 3 | 0.1677 | 0.3377 | 0.0389 | 0.1007 | 0.4120 | 0.5737 |
| dental visits | 1 | 0.1423 | 0.2361 | 0.0713 | 0.1035 | 0.2387 | 0.3130 |
| dental visits | 2 | 0.1453 | 0.2528 | 0.0947 | 0.1538 | 0.3484 | 0.5089 |
| dental visits | 3 | 0.2499 | 0.5821 | 0.1272 | 0.2031 | 0.4438 | 0.6494 |
| inpatient facility | 1 | 0.2110 | 0.4049 | 0.1299 | 0.1834 | 0.2928 | 0.4152 |
| inpatient facility | 2 | 0.2920 | 0.5901 | 0.2056 | 0.3031 | 0.4618 | 0.7730 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| inpatient facility | 3 | 0.3495 | 0.8165 | 0.2404 | 0.4383 | 0.5629 | 0.7007 |
| office based visits | 1 | 0.1091 | 0.1621 | 0.0330 | 0.0514 | 0.2138 | 0.3180 |
| office based visits | 2 | 0.1417 | 0.2558 | 0.0468 | 0.0765 | 0.3212 | 0.4930 |
| office based visits | 3 | 0.1899 | 0.2571 | 0.0603 | 0.1372 | 0.4060 | 0.5495 |
| outpatient doctors | 1 | 0.1746 | 0.2661 | 0.1231 | 0.1761 | 0.2782 | 0.4306 |
| outpatient doctors | 2 | 0.3380 | 0.6895 | 0.2111 | 0.3783 | 0.4673 | 0.7005 |
| outpatient doctors | 3 | 0.3764 | 0.7446 | 0.2794 | 0.4949 | 0.5280 | 0.7346 |
| prescription drugs | 1 | 0.0953 | 0.1923 | 0.0389 | 0.0532 | 0.2305 | 0.4494 |
| prescription drugs | 2 | 0.1290 | 0.2104 | 0.0531 | 0.0912 | 0.3401 | 0.5310 |
| prescription drugs | 3 | 0.1696 | 0.2695 | 0.0667 | 0.1392 | 0.4025 | 0.5868 |

Table 1 shows:

- State level estimates with acceptable precision can be made for some states from the MEPS -HC, but there are still many estimates of poor precision. This can be seen from the maximum rse values for many of the groups. (Note: RSE ge 0.30 is considered as poor.)

- Estimates for the percent of persons with each type of expenditure have good precision, while the total expenditure estimates are of uniformly poor quality.

- The estimates are generally of best quality for expenditure types which affect the most people and thus have the greatest sample, such as, all types combined or office based visits, while the worst are inpatient facility and outpatient doctor estimates because the numbers of sample persons with these expenditure types are very small. None of the size groups of states could be published for the latter two types of expenditures.

- The estimates decline in precision as the size of states decreases.

- With a goal of a maximum rse's of 20%, for the majority of the cases, only estimates for the 10 largest states could be produced.

Most of these results with respect to the reliability of the estimates could be expected. Most are directly related to expected sample. For any type of expenditure the percent of persons with an expenditure is the best estimates because this estimate is based upon the entire sample and the distribution. The conditional mean and total expenditure estimates are based upon subsets of the sample in each state. Further, these estimates are based upon the distribution of expenditures which can be highly skewed. The extremely poor quality of the total expenditure estimates versus the conditional mean estimates, can be attributed to the fact that the between PSU variances of population totals are much higher than between PSU variances of average usage.

Design-Based Estimates with Weights Post Stratified by State

After review of the first set of results, it was decided that the estimates could be improved using weights that were poststratified to CPS population totals at the state level. For each state the non-response adjusted weights were post stratified by state, age, race and gender. The use of these weights produced a marked improvement in the precision of the results.

**TABLE 2**
**Average and Maximum Relative Standard Errors by State Size Group for Typical Estimates: State Level Post Stratification: MEPS - HC, 2002**

| | | Conditional Mean Expenditures | | Percent of Persons with Expenditure | | Total Expenditures | |
|---|---|---|---|---|---|---|---|
| **Expenditure Type** | **Size Group** | **Mean Rse** | **Max Rse** | **Mean Rse** | **Max Rse** | **Mean Rse** | **Max Rse** |
| all types combined | 1 | 0.0744 | 0.1126 | 0.0152 | 0.0206 | 0.0756 | 0.1181 |
| all types combined | 2 | 0.1072 | 0.2112 | 0.0198 | 0.0283 | 0.1085 | 0.2179 |
| all types combined | 3 | 0.1250 | 0.2635 | 0.0256 | 0.0558 | 0.1340 | 0.2582 |
| dental visits | 1 | 0.1128 | 0.2032 | 0.0512 | 0.0794 | 0.1288 | 0.2214 |
| dental visits | 2 | 0.1123 | 0.1947 | 0.0703 | 0.1050 | 0.1252 | 0.1974 |
| dental visits | 3 | 0.1804 | 0.4529 | 0.0921 | 0.1366 | 0.1988 | 0.4655 |
| inpatient facility | 1 | 0.1631 | 0.2852 | 0.0972 | 0.1482 | 0.1759 | 0.2896 |
| inpatient facility | 2 | 0.2229 | 0.5188 | 0.1427 | 0.2009 | 0.2738 | 0.5763 |
| inpatient facility | 3 | 0.2591 | 0.6084 | 0.1870 | 0.3432 | 0.3183 | 0.6300 |
| office based visits | 1 | 0.0869 | 0.1217 | 0.0227 | 0.0349 | 0.0887 | 0.1252 |
| office based visits | 2 | 0.1037 | 0.1751 | 0.0335 | 0.0589 | 0.1112 | 0.1827 |
| office based visits | 3 | 0.1376 | 0.2090 | 0.0429 | 0.0829 | 0.1564 | 0.2494 |
| outpatient doctors | 1 | 0.1399 | 0.2267 | 0.0883 | 0.1278 | 0.1574 | 0.2294 |
| outpatient doctors | 2 | 0.2406 | 0.3997 | 0.1561 | 0.2291 | 0.2717 | 0.3809 |
| outpatient doctors | 3 | 0.2546 | 0.4987 | 0.2078 | 0.3453 | 0.3061 | 0.6082 |
| prescription drugs | 1 | 0.0674 | 0.1496 | 0.0254 | 0.0357 | 0.0743 | 0.1534 |
| prescription drugs | 2 | 0.0890 | 0.1529 | 0.0349 | 0.0582 | 0.0976 | 0.1592 |
| prescription drugs | 3 | 0.1235 | 0.2644 | 0.0418 | 0.1015 | 0.1353 | 0.2463 |

The use of weights post stratified with state population totals yielded the following results shown in Table 2.

- Results are uniformly better than those in Table 1.

- Of special interest are the results for total expenditures for each type. These estimates are now of approximately the same quality as those for the conditional mean expenditures for the same type of expenditure. This improvement is likely the results of the stabilization of totals from the use of state specific post stratification. This post stratification essentially makes the estimates of totals a ration estimate which use the average usage times the mean conditional expenditure times an outside population total for each state. As we saw earlier the rse of average usage and mean conditional expenditure estimates were more precise and this change in the estimates of total expenditures results in estimates with rse's closer to those of the first two types of estimates. Nevertheless, there are still estimates with very large rse's.

- Although improved, estimates for inpatient facility and outpatient doctors are still problematic.

- For all other expenditure groups, all types combined, office based visits, dental visits and prescription drugs, the improvements are such that one could make estimates for the 20 largest states in size groups 1 and 2, the 20 largest states, with very few estimates with an rse greater than 20%.

Estimates in an AHRQ report titled "*Estimates of Health Care Expenditures for the 10 Largest States, 2000*" are based on this methodology.

<u>Composite Estimation</u>

Given that we have produced estimates for every state, a small area estimation approach could potentially be used to adjust and improve these estimates by "borrowing strength across states". In this case one can consider a random effects model or a Bayesian approach based upon such a model. (Ghoush and Rao, 1994) However, it was decided to use a method which makes no assumptions about the relationships among estimates and is simple to apply across a large number of estimates.

It was decided to apply a composite estimation technique to estimates of the conditional mean expenditures and percents with an expenditure. Strength can be borrowed from sample estimates at the Census Division level, the regional level or the national level. This type of estimate uses a weighted average $Y_c = w\ \hat{Y}_1 + (1-w\ )\hat{Y}_2$ where $Y_1$ and $Y_2$ are usually a synthetic and direct estimates of the same item. The weight is determined by minimizing the (MSE) of the linear combination of estimators. In this case the sample estimate for a larger geographic area was chosen as the synthetic estimate and the state estimate as the direct estimate. Under these conditions assuming that the state estimate is an unbiased estimate of the state value, then the value of w which minimizes the mean squared error (mse) of the composite estimator is:

$$w = \frac{\left(\mathrm{var}(\hat{Y}_m) - \mathrm{cov}(\hat{Y}_{m,} \hat{Y}_d)\right)}{\left(\mathrm{var}(\hat{Y}_m) + \mathrm{var}(\hat{Y}_d) - 2\,\mathrm{cov}(\hat{Y}_{m,} \hat{Y}_d) + bias^2\right)}$$

where m denotes the design based state estimator and d the estimator for the larger geographic area. Bias in this case is the squared difference in expected values of the state and synthetic estimates,

$$(E(\hat{Y}_m) - E(\hat{Y}_d))^2$$

This result can be obtained simply by taking the MSE of the composite estimate and using differentiation to calculate the value of w which minimizes the result.

The terms in the numerator can be estimated using the half samples. The bottom term can be estimated using the square of the difference of the two estimators. However, that estimate can be very unstable. Thus, a method using the sum of squared differences of the half sample estimates was developed to estimate the denominator term, which is the variance of the difference of the two estimators plus the squared difference in their expected values. Using these estimates for w, new estimates and their mse's and rse's were calculated using

$$Var(Y_c) = w^2 Var(Y_d) + (1-w)^2 Var(Y_s) - 2w(1-w)C(Y_d, Y_s)$$
$$MSE(Y_c) = w^2 Var(Y_d) + (1-w)^2 Var(Y_m) + 2w(1-w)Cov(Y_d, Y_m) + w^2 bias^2$$

This mse was estimated using the individual parts developed in the calculation of w. Of special interest is the estimate of the bias. One can use the fact that

$$E\left(Y_d - Y_s\right)^2 = Var(Y_d - Y_s) + bias^2$$

One can just take the difference of the two estimates squared and subtract an estimate of the variance of the difference of the two estimates to obtain an estimate of the bias. However, this is an unstable estimate. We instead take advantage of the following expected value for the difference of the two estimates for the ith half sample.

$$E\left(Y_{di} - Y_{si}\right)^2 = 2 * Var(Y_d - Y_s) + bias^2$$

Thus we average the values of the difference squared for each half sample and subtract the standard estimate of twice the variance to obtain an estimate of the bias.

Because the value of w is an estimate, the sample estimate of this variance is only an estimate of the variance of the estimator given the estimate of w. This does not account for the expected variance due the estimation of w. To account for this variation, w was estimated using groups of half samples. Specifically, w was estimated using these sets of half samples and half sample estimates of the composite were made by varying the estimates of w with the full sample values of the model and division estimates. Addition of this term was prompted by bias found by Prassad and Rao (1990) in formulas which didn't consider the variation caused by estimation of w. This term did not add large sums to the overall errors. This indicates that the estimates of variance and bias are generally stable. However, when the value of w was very close to 1 or 0, the estimates of w became less stable. It was decided that the value of w would be limited to values between, .1 and .9 for the final composite estimates currently produced.

Table 3 below shows values, obtained using the composite estimation technique, comparable to those in Tables 1 and 2 for conditional mean expenditures and percent with the expenditure type.

The synthetic estimate used to create these estimates was the regional estimate.  This synthetic estimate was chosen because it gave better results than using the Census division and about the same quality as combining state and national estimates while not changing the original value of the state estimates to the same degree as the using the national estimates as the synthetic estimate.

We should note that as with any set of error estimates made using sampling data, the estimates of mean squared errors, used have errors also. Thus, some of the composite estimates could have less quality than the numbers indicate. This is true when making estimates of error for any set of estimates. However, we base our final evaluation of the quality of the composite estimates when compared to the other unbiased estimators, not on the results for just one estimate, but on the fact that as a group the estimates of errors for the composite estimators are almost uniformly better than those for the more standard design based estimates.

**TABLE 3**
**Average and Maximum Relative Mean Squared Errors by State Size Group for Typical Estimates: Composite Estimation Using Regional Estimates: MEPS - HC**

| | | Conditional Mean Expenditures | | Percent of Persons with Expenditure | |
|---|---|---|---|---|---|
| **Expenditure Type** | **Size Group** | **Mean Rmse** | **Max Rmse** | **Mean Rmse** | **Max Rmse** |
| all types combined | 1 | 0.0587 | 0.0914 | 0.0107 | 0.0189 |
| all types combined | 2 | 0.0533 | 0.1116 | 0.0117 | 0.0176 |
| all types combined | 3 | 0.0758 | 0.1556 | 0.0143 | 0.0241 |
| dental visits | 1 | 0.0699 | 0.1032 | 0.0418 | 0.0629 |
| dental visits | 2 | 0.0688 | 0.1311 | 0.0536 | 0.0682 |
| dental visits | 3 | 0.0912 | 0.1742 | 0.0719 | 0.1378 |
| inpatient facility | 1 | 0.1086 | 0.1441 | 0.0694 | 0.0989 |
| inpatient facility | 2 | 0.1217 | 0.1521 | 0.0587 | 0.1149 |
| inpatient facility | 3 | 0.1750 | 0.3330 | 0.0872 | 0.2130 |
| office based visits | 1 | 0.0598 | 0.1112 | 0.0163 | 0.0272 |
| office based visits | 2 | 0.0609 | 0.1009 | 0.0182 | 0.0359 |
| office based visits | 3 | 0.0657 | 0.1240 | 0.0261 | 0.0538 |
| outpatient doctors | 1 | 0.0866 | 0.1223 | 0.0747 | 0.1212 |
| outpatient doctors | 2 | 0.1119 | 0.2355 | 0.1243 | 0.1689 |
| outpatient doctors | 3 | 0.1639 | 0.4506 | 0.1778 | 0.3118 |
| prescription drugs | 1 | 0.0497 | 0.0841 | 0.0193 | 0.0252 |
| prescription drugs | 2 | 0.0536 | 0.1053 | 0.0193 | 0.0459 |
| prescription drugs | 3 | 0.0747 | 0.2189 | 0.0267 | 0.0513 |

One can see from Table 3, that the process this technique provides several advantages.

- In spite of their biased nature, estimates have uniformly better estimated relative mean squared errors than the previous two methods.

- Improvement was greatest where it was needed most, i.e. in size groups 2 and 3 and inpatient facility and outpatient doctors.

- Improvements were such that one could make estimates for all expenditure types for State size groups 1 and 2, the 20 largest states and have very few estimates with greater than a 20% relative standard error and none with a relative standard error greater than 30%. With the exception of errors for inpatient facility and outpatient doctors, the vast majority of the estimates for the 20 largest states have relative errors of less than 10%.

- For all but the least common types of expenditures, inpatient facility and outpatient doctors, most of the estimates for the set of the smallest States, size group 3, are acceptable using a 10% relative error as the standard of acceptance. Few of these estimates for the smallest states have relative error measures of over 20%.

One should note that although estimates of totals are not evaluated, if one has good estimates of means and proportions, one can make estimates of totals by multiplying means by total population estimates from other sources.

**Conclusions and Recommendations**

We made two sets of direct state estimates with 2002 MEPS-HC data for the 30 largest states. The first set was produced using standard nationally post stratified weights and the second used weights post stratified within each of the largest states. Each set of estimates included estimates for 6 types of expenditures and 3 measures, an estimate for total expenditures and estimates for conditional mean expenditure per person with an expenditure and for the percent of persons with an expenditure. After this, estimates for the same 6 types of expenditures were made for the mean and the percent with an expenditure using a **biased** small area technique where strength was borrowed for state estimates from data for the entire region. Several patterns of information surfaced:

- Estimates decreased in quality as the population size of the state decreased and the number of PSU's decreased.

- The best estimates in any group were for percent of persons who had expenditures. Estimates of error for the conditional mean expenditure and total expenditures were correlated with the percents of persons who had the expenditure, i.e., sample size used.

- Overall, the relative errors of the estimates were best for the small area technique and worst based on the Nationally stratified weights.

- One can make estimates for the 20 largest states for the more common expenditures with the state post stratified weights, and one can generally make improved estimates with the small area technique for each state for all the expenditure types tested.

The research was very successful and confirms the feasibility for making state estimates with the MEPS-HC to help inform health policy decisions at the state level. Given these results, it seems that estimates could be produced for additional survey variables at the State level for the 20 largest States. Efforts should be focused on items which affect a large enough portion of the population, so that enough sample is available to produce estimates with acceptable quality. Among the items that might be considered are expenditures for obese and overweight persons, persons with private health insurance or persons without health insurance, all subsets which might have a large enough sample to produce reliable estimates.

Given the simplicity of the process and that development of state stratified weights and software to produce these estimates have been completed, additional estimates can and should be produced and assessed to determine how many state level estimates can be produced on a regular basis in the future.

## Acknowledgements

The author would like to thank Trena Ezzati-Rice and Steve Machlin for their valuable ideas and comments which were used freely in the production of this work.

**References**


Botman, M, TF Moore, CL Moriarity and VL Parsons. Design and Estimation for National Health Interview Survey, 1995 - 2004. National Center for Health Statistics, Vital Health and Statistics 2(130) 2000.

Census Bureau. Web site a: www.sipp.census.gov/sipp/sample.html.

Census Bureau. Web site b: http://www.census.gov/hhes/www/housing/ahs/statedata.html

Census Bureau. Web site c: http://www.census.gov/hhes/www/poverty.html#sipp

Census Bureau. Web site d: www.census.gov/hhes/www/housing/ahs/ahs01/appendixb.pdf.

Cohen SB. Sample Design of the 1997 MEPS_HC. Rockville (MD); AHRQ: 2000. Meps Methodology Report No 11 AHRQ Pub No 01-0001.

Cochran WG. Sampling techniques. New York: John Wiley and Sons: 1977.

DeNavas-Walt, Carmen, Bernadette D. Proctor and Robert J. Mills. U.S. Census Bureau, Current Population Reports P60-226. *Income, Poverty and Health Insurance Coverage in the United states: 2003.* U.S. Government Printing Office, 2004.

Ghosh M, and Rao, JNK (1994). Small area estimation: an appraisal. *Statistical Sciences*, Vol. 9, No 1, 55-93.

Kaiser Family Foundation (2004). *Employer Health Benefit, Annual Survey.* Menlo Park, CA.

Kostanich, DL, and CS Dippo(2002). *Current Population Survey: Design and Methodology,* Technical Paper 63RV, Washington, DC: U.S. Government Printing Office.

Machlin, S. R. and Sommers, J. P. Estimates of Health Care Expenditures for the 10 Largest States, 2002. Statistical Brief #69. February 2005. Agency for Healthcare Research and Quality, Rockville, Md. http://www.meps.ahrq. gov/papers/st69/stat69.htm

Medical Expenditure Panel Survey. Website: http://meps/CompendiumTables/TC_TOC.htm.

National Association of State Budget Officers (2003). *State Expenditure Report.* Washington, DC.

National Center for Health Statistics. Web Site: www/cdc.gov/nchs/nhis.htm.

Prasad, NGN and Rao, JNK (1990). The estimation of mean squared errors of small area estimators, Journal of American Statistical Association, 85, 163-171.

Wolter KM. Introduction to Variance Estimation. New York: Springer-Verlag: 1985.