VARIANCE ESTIMATION FOR CURRENT POPULATION SURVEY SMALL AREA LABOR FORCE ESTIMATES

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Introduction

More and more users of public data sets desire measures of the reliability of the information these data sets provide. To help answer this need, the Bureau of the Census recently created a data set of replicate weights. These weights allow users to compute variance estimates for 1987 labor force data from the Current Population Survey (CPS), a monthly household survey the Census Bureau conducts for the Bureau of Labor Statistics (BLS). The Census Bureau computed the replicate weights by generalized replication, a variance estimation method developed by Dr. Robert Fay and used for several U.S. government surveys. Because of the high cost of computing replicate weights for the CPS, Census only computes them once every ten years–that is, once each time the CPS sample is redesigned–using one year's data. Generalized variance functions (GVF's) are used to generalize the resulting variance estimates across time for the duration of the sample design. Census computed the 1987 replicate weights primarily for estimating variances of national CPS estimates and used them to compute GVF's for national data. The replicate weights in the public data set may be used to estimate variances and covariances of any statistics computed from the 1987 CPS data.

Part I of this paper explains how the CPS replicate weights were computed and how they may be used to estimate variances. Part II provides an example of their use for subnational variance estimation: I used the replicate weights to evaluate the BLS method of standard error estimation for state labor force data.

PART I
THE CPS REPLICATE WEIGHTS

Section 1.1: Computing the Weights

Creating "SECU's"

The CPS sample is a two-stage cluster sample of housing units. Most of the primary sampling units (PSU's) are metropolitan areas, large counties, or groups of smaller, contiguous counties. The Census Bureau stratifies the PSU's and selects one PSU from each stratum, with probability of selection proportional to the population size the of the PSU. PSU's in strata by themselves–generally large metropolitan areas–are called self-representing (SR). The remaining PSU's are called non-self-representing (NSR), since each one chosen represents not only itself but its entire stratum. In the second stage of sampling, clusters of about four housing units are selected systematically from the sample PSU's, using the address list from the most recent decennial census as a basic sampling frame. (For a detailed though somewhat outdated discussion of the CPS sample design, see Technical Paper 40 (1978).)

The replication (or half-sampling) method of variance estimation was originally developed assuming a two-PSU-per-stratum design, PSU's within a stratum being about equal in size. Since the CPS employs a one-PSU-per-stratum design and PSU's may vary in population size, Census created Standard Error Computing Units (SECU's) or "pseudo-strata," each containing two or three panels ("pseudo-PSU's"), the panels being about equal in population size.

To create SECU's for NSR strata, Census collapsed NSR PSU's into groups of two–creating "NSR pairs"–and three–creating "NSR triples." Because of this collapsing, variance estimates computed from the replicate weights include a "between-stratum" component of variance, not actually present in CPS estimates. Census tried, however, to collapse PSU's in a way that minimized the upward bias in the variance estimates. For a description of the collapsing method used, see Canamucio (1987).

Since SR PSU's are generally much larger than NSR PSU's, each was divided into several pieces–SR SECU's–each comprising nine to sixteen clusters of housing units. Each SR SECU was then divided into two panels, which served as pseudo-PSU's in the replication procedure.

In dividing SR SECU's into panels, Census had to consider the CPS "4-8-4" sample rotation scheme. Under this scheme, a new group of households enters the CPS sample each month. Households remain in sample for four months, leave the sample for eight months, and then reenter the sample for the following four months. Thus each month's CPS data include responses from households in each of eight rotation groups, which may be identified by the number of months they have been in the sample (first month-in-sample, second month-in-sample, etc.). Since estimates for households in different month-in-sample categories reveal a relative bias—higher unemployment rates are obtained for respondents in their first and fifth months in sample (see Bailar (1975))—Census divided each SR SECU into panels that were approximately balanced, both by size and by rotation group distribution. (This procedure is described by Kostanich (1987).) But since SR SECU's may contain as few as nine clusters of housing units, complete balancing of panels by rotation group was not always possible. Variance estimates computed from the replicate weights may therefore reflect a slight upward bias due to the rotation group bias in the CPS.

Assigning Replicate Factors to SECU Panels

To assign replicate factors to the SECU panels—the PSU's or pseudo-PSU's within the SECU's—Census used the generalized replication theory developed by Fay (1984, 1989). The method used for each SECU type was slightly different.

The procedure for assigning replicate factors to the panels of SR SECU's involved a 48 X 48 Hadamard matrix (with the first column of 1's removed) and a random number n, which served as a starting column number for assigning matrix columns to SECU's. The nth column of the matrix was assigned to the first SECU on a list of SR SECU's. The (n+1)st column was assigned to the next SR SECU on the list and so forth—one column per SECU. Each matrix column contained 48 entries (1's and -1's) which determined the replicate factors according to formula (2.5) in Fay (1989) as follows:

Let x_k be an estimate of total (for some characteristic) for the kth panel of a SECU containing two panels (k = 1, 2). An estimate of the variance of the SECU total $x = x_1 + x_2$ is:

$$V = (x_1 - x_2)^2,$$

which may be written as the quadratic form

$$V = \mathbf{x}^T C \mathbf{x}, \qquad (1.1.1)$$

where

$$\mathbf{x} = [x_1, x_2]^T, \text{ and}$$

$$C = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}.$$

C has one positive eigenvalue, $\lambda = 2$, and the corresponding normal eigenvector is $\nu = [(1/2)^{1/2}, -([1/2]^{1/2})]^T$.

Let

H_{ir} = the entry in the Hadamard matrix for the rth replicate (or matrix row) for SECU i;

r = 1, 2,..., 48;

f_{irk} = the replicate factor for replicate r and panel k of SECU i; *and*

$\mathbf{f}_{ir} = [f_{ir1}, f_{ir2}]^T$.

Formula (2.5) from Fay (1989) gives the vector of replicate factors $\mathbf{f}_{ir}$ as:

$$\mathbf{f}_{ir} = \mathbf{1} + c \sum_{m=1}^{M} H_{irm} \lambda_m^{1/2} \nu_m, \qquad (1.1.2)$$

where M is the number of positive eigenvalues of C, counting multiplicities. In this case, M = 1 and the formula reduces to:

$$\mathbf{f}_{ir} = \mathbf{1}_2 + c\, H_{ir} \lambda^{1/2} \nu,$$

$$= [1, 1]^T + c\, H_{ir} (2^{1/2}) [(1/2)^{1/2}, -([1/2]^{1/2})]^T$$

$$= [1, 1]^T + c\, H_{ir} [1, -1]^T.$$

The constant c was chosen to be 1/2. This choice was deemed suitable for a number of surveys conducted by the Census Bureau; it is a "half-way" value between standard balanced repeated replication (c=1) and a Taylor Series linearization procedure (c=0). With these values, the replicate factors from the formula are:

f_{ir1} = 3/2 and f_{ir2} = 1/2, when H_{ir} = 1, *and*

f_{ir1} = 1/2 and f_{ir2} = 3/2, when H_{ir} = -1.

Since NSR PSU's may vary in size, the replicate factors derived for SR SECU's were adjusted to account for differences in PSU size and then applied to the NSR SECU's, using a similar procedure for assigning Hadamard matrix columns to SECU's.

Each NSR triple comprised three NSR PSU's. Replicate factors for the NSR triples were derived directly from (1.1.2); the derivation (Fay (1987)) is the same as that given above for the replicate factors for SR SECU's, but with three panels instead of two. A variance estimate for the SECU total $x = x_1 + x_2 + x_3$ is:

$$V = 3/2\ \Sigma_k\ [x_k - 1/3\ \Sigma_k\ x_k]^2,$$

where x_k is the sample estimate for panel k (k = 1, 2, 3). This may be written in quadratic form, as in (1.1.1), with

$$\mathbf{x}^T = [x_1, x_2, x_3] \quad \text{and}$$

$$C = \begin{bmatrix} 1 & -1/2 & -1/2 \\ -1/2 & 1 & -1/2 \\ -1/2 & -1/2 & 1 \end{bmatrix}.$$

In general, (1.1.2) requires that the number of Hadamard matrix entries corresponding to each replicate equal the number of positive eigenvalues of C, counting multiplicities (M). In this case, C has one positive eigenvalue, λ = 3/2, of multiplicity 2, so two matrix columns were assigned to each NSR triple. Orthonormal eigenvectors corresponding to $\lambda = 3/2$ are $\nu_1 = (3/2)^{1/2}(1, -1/2, -1/2)$ and $\nu_2 = (1/2)^{1/2}(0, 1, -1)$.

Let

- H_{ir1} = the entry in the Hadamard matrix in the first of two columns for the rth replicate for SECU i;
- H_{ir2} = the entry in the Hadamard matrix in the second of two columns for the rth replicate for SECU i;
- f_{irk} = the replicate factor for replicate r and panel k of SECU i (k = 1, 2, 3); *and*
- $\mathbf{f}_{ir} = [f_{ir1}, f_{ir2}, f_{ir3}]^T$.

Plugging these values into (1.1.2) gives

$$\mathbf{f}_{ir} = \mathbf{1}_3 + 1/2 \sum_{m=1}^{2} H_{irm}\ \lambda^{1/2}\nu_m,$$

where $\lambda = 3/2$,
$\nu_1 = (3/2)^{1/2}(1, -1/2, -1/2)$, and
$\nu_2 = (1/2)^{1/2}(0, 1, -1)$,

which yields the following table of replicate factors:

	(H_{ir1}, H_{ir2})			
	(1,1)	(1,-1)	(-1,1)	(-1,-1)
f_{ir1}	1.5	1.5	0.5	0.5
f_{ir2}	1.183	0.317	1.683	0.816
f_{ir3}	0.317	1.183	0.817	1.683

<u>Computing Replicate Weights</u>

The replicate factors were applied to the sampling (or base) weights of person records on the CPS data file, creating 48 replicate samples. The full sample and the 48 replicate samples were then processed through the CPS estimation procedures (which include a noninterview adjustment and two other ratio adjustments) to produce a set of 49 weights—the full sample weight and 48 replicate weights—for each sample person. These weights may be used to estimate variances and covariances for any statistics computed from the 1987 CPS data.

Section 1.2: Using the Replicate Weights

Estimating variances from the replicate weights is easy. First we compute a *replicate estimate* for each characteristic g and replicate i:

$$x_{gi} = \Sigma_l\ w_{gil},$$

where w_{gil} is the replicate weight for sample person l having characteristic g. A variance estimator for the *full sample estimate*, (or 0th replicate estimate) x_g is:

$$\mathrm{var}\,(x_g) = b_R \sum_{i=1}^{R} (x_{gi} - x_g)^2,$$

where b_R = $1/Rc^2$, and R is the number of replicates. Here R = 48, and c = 1/2, so b_R = 4/48, and the variance estimator is:

$$\mathrm{var}\,(x_g) = (4/48) \sum_{i=1}^{48} (x_{gi} - x_g)^2.$$

Variances for CPS Composite Estimates

Variance estimates for CPS composite estimates may be computed by compositing the monthly estimates for each replicate sample and applying the variance formula above. Variance estimates from the first two months, however, should be disregarded: these data months are needed to initialize the composite estimator.

PART II
APPLYING THE VARIANCE ESTIMATION SYSTEM TO STATE DATA

Section 2.1: The Current BLS Method of State Variance Estimation

The GVF's the BLS uses for state variance estimation are based on design effects estimated from national data collected under the 1970 CPS design. Here I derive the state GVF's and outline the main assumptions implied.

Derivation of Current State GVF's

Since the CPS employs a two-stage sample design, the variance σ^2 of a CPS estimate of total includes both within-PSU and between-PSU components; that is,

$$\sigma^2 = \sigma^2_W + \sigma^2_B,$$

where σ^2_W and σ^2_B are the within- and between-PSU components of variance. The national *within-PSU design effect* (de_{NW}) is defined as the ratio of the within-PSU variance of a CPS estimate of total, assuming the CPS sample design, to the total variance of the estimate, assuming simple random sampling.

σ^2_W may be estimated by:

$$\hat{\sigma}^2_W = de_{SW}\,(N/n)\,N\,(y/N)\,[1-(y/N)],$$

where de_{SW} is the state within-PSU design effect, estimated from de_{NW} by adjusting for differences in noninterview rate.

Let $P = \sigma^2_B/\sigma^2$. Then $\sigma^2_B = P\,\sigma^2$, and σ^2 may be estimated by:

$$\hat{\sigma}^2 = \hat{\sigma}^2_W / (1 - p)$$
$$= de_{SW}\,(N/n)\,(y)\,[1-(y/N)] / (1 - p).$$

where p, an estimate of P, is computed from decennial census data.

Assumptions:
1) The within-PSU design effect calculated from national data is assumed to roughly equal the corresponding state design effects.
2) $P = \sigma^2_B/\sigma^2$ is assumed constant across time.

In evaluating this method, I tested assumption (1) above. Assumption (2) may be tested only by estimating state within-PSU variances. Since the replicate weights allow only estimation of the total variance of a given labor force characteristic, I could not test assumption (2).

Section 2.2: Using the Replicate Weights for State Variance Estimation

Variance estimates computed from the replicate weights for a given state are less biased than variance estimates computed by the GVF method described above, so I used them to evaluate the bias associated with the GVF method. As mentioned, however, the replicate weights were computed primarily for use at the national level. Though they are also suitable for estimating variances for the most populous states, limitations arise when they are used to estimate variances for small or rural states.

Stability of Variance Estimates

For small or rural areas, variance estimates computed from the replicate weights are relatively unstable because they do not have many *degrees of freedom*. The number of degrees of freedom of a small area variance estimate is the rank of the matrix formed by placing side by side all Hadamard matrix columns assigned to SECU's in that particular small area. Since each orthogonal row of this matrix determines an independent replicate estimate, the rank of the matrix is the number of independent replicate estimates. If this number is small, the resulting variance estimates will be unstable. And if many SECU's in the area are assigned to some columns of the Hadamard matrix while few are assigned to other columns, the replicates will be poorly balanced; this also decreases the stability of the variance estimates.

The following formula provides an estimate of the coefficient of variation (CV) of a variance estimate for a state or for a group of states, taking into account the effect of differing sampling ratios between states and the effect of differences in the number of SECU's assigned to the various columns of the Hadamard matrix.

$$CV(var) = \frac{\left[2 \Sigma_H \left(\Sigma_S W_S^2 m_{SH}\right)^2\right]^{1/2}}{\left[\Sigma_h \Sigma_S W_S^2 m_{SH}\right]}, \qquad (2.2.1)$$

where W_S = the sampling interval (or base weight) for state S, *and*
m_{SH} = the number of SECU's from state S assigned to column H of the Hadamard matrix.

Use of (2.2.1) for approximating the stability of CPS variance estimates is optimistic, since the formula assumes that within-SECU variance is the same for all SECU's, an assumption which may not hold for the CPS. A SECU comprising three NSR PSU's, for example, may have a different within-SECU variance than a SECU representing a much smaller geographic area in an SR PSU. Though each SECU may contribute one degree of freedom to the variance estimate, their effect on the stability of the estimate may differ. Because of confidentiality laws, however, data that might allow further examination of within-SECU variances cannot be provided in a public data set.

Table 1 gives estimated CV's for state variance estimates, along with the corresponding numbers of SECU's and degrees of freedom for the eleven states having the lowest CV's. Estimated CV's of the variance estimates for the remaining states fell between thirty and fifty percent.

Evaluating the Current State GVF's

In order to evaluate the state variance estimation method described in Section 2.1, I used the replicate weights to compute variance estimates for monthly 1987 state employment and unemployment totals. I compared these to the corresponding standard error estimates computed by the current GVF method.

Because of the instability of the replication variance estimates for small states, I used only data from the eleven states having the most stable variance estimates–the eleven states listed in Table 1–in my analysis.

From the state variances estimated by replication, I computed monthly design effects for state employment and unemployment totals. I averaged the monthly design effects for March through December (using the first two data months to initialize the CPS composite estimator) and computed monthly 1987 standard error estimates from these average design effects.

Using the estimated CV's from Table 1, I constructed approximate 1σ confidence intervals around the 1987 total employment and unemployment standard error estimates computed directly from the replicate weights. Then I examined standard error estimates computed by

1) the current state GVF method *and*
2) the new method: using state design effects computed from the replicate weights

to see whether or not they fell within these intervals.

The results for Michigan were typical: as figures 1 and 2 show, the employment standard errors computed by the current method fell below the lower confidence limits, while most of the standard errors for unemployment computed by the current and new methods fell within the intervals. For most states, there was little difference between the unemployment standard errors computed by the current and new methods, indicating that the bias associated with the current unemployment GVF's may be reasonably low. For every state examined, however, employment standard error estimates computed by the new method were noticeably higher than those computed by the current method.

Analyzing State Unemployment Design Effects

Since my analysis using confidence intervals indicated that unemployment design effect varied little across states, I wanted to test for significant differences between the state and national unemployment design effects. In order to justify the use of a t-test for this purpose, I first examined the correlation structure and distribution of the ten monthly observations (March through December, 1987) of state unemployment design effect for the eleven large states.

CPS sample overlap and composite estimation cause positive correlation between CPS unemployment estimates from consecutive months. But the correlation between design effects computed from consecutive months' data may reasonably be expected to be lower than the correlation between monthly estimates of total unemployment. To examine the autocorrelation of the monthly unemployment design effects, I standardized the observations from each state by subtracting the mean and dividing by the estimated standard error of the design effect for that state. I paired the observations (within state) from consecutive months to obtain 97 ordered pairs of observations. (Nine from each of the eleven large states, minus two from Florida--I had deleted one outlying observation from the Florida data.) The Spearman correlation coefficient for these pairs of observations was about -0.128, indicating no significant positive correlation. Since sample overlap and composite estimation were the only suspected sources of dependence between the observations (in particular, no negative correlation was suspected), it seemed reasonable to assume that the monthly observations of unemployment design effect were essentially independent.

To test for normality, I computed a Shapiro-Wilks statistic for the ten monthly observations of design effect from each of the eleven large states. For Ohio and Texas, the p-values for the normality test were less than 0.05, so I limited further analysis to data from the remaining nine states.

For each of the nine large states, I used a t-test to test for differences between (a) state unemployment design effect and (b) the national unemployment design effect, adjusted for differences in noninterview rate--that is, the design effect used in the current state GVF's.

The ratio of between-PSU variance to total variance differs by state, so I performed the test on the state within-PSU design effects, estimated by

$$de_{SW} = de_{STA}\,(1-p_S), \text{ where}$$

de_{STA} = average total design effect for state S, estimated from the replicate weights,
p_S = estimated ratio of between-PSU variance to total variance, mentioned in Section 2.1, for state S, *and*
de_{SW} = estimated within-PSU design effect for state S.

For each state, I computed a t-statistic to test the hypothesis:

$$H_0:\ \mu_S = 0 \quad \text{vs.} \quad H_A:\ |\mu_S| > 0\ , \text{ where}$$

$\mu_S = de_{SW} - de_N\, f_S$,
de_N = national within-PSU design effect for unemployment,
de_{SW} = estimated state within-PSU design effect for unemployment, *and*
f_S = the adjustment factor for differences between state and national noninterview rates.

Table 2 provides the resulting t-statistics and p-values along with the state within-PSU design effects and their standard errors. For all states tested, the p-values were too high to justify rejecting H_0.

Assuming a significance level of 0.05, I estimated the power of the t-test for each state under three simple alternative hypotheses:

$$H_1:\ |\mu_S| = (0.1)\, de_N\, f_S;$$

$$H_2:\ |\mu_S| = (0.2)\, de_N\, f_S;$$

$$H_3:\ |\mu_S| = (0.3)\, de_N\, f_S.$$

The estimates of power appear in Table 3. Good power was obtained for most states for the test of H_0 against H_3; the power of the test of H_0 against H_2 was also reasonably good in many cases.

<u>Interpreting the Results</u>

For all states for which I performed t-tests, I failed to reject H_0 at the 0.05 level of significance. Though I did not reject H_0 for Florida, Illinois, and New York, the probability of type II error was high for these states. Possible reasons for this include:

1) The within-PSU unemployment design effects for the states listed above actually exceed the national unemployment design effect.
2) The ratio of between-PSU variance to total variance for these states increased between 1980 and 1987, artificially inflating the estimated state within-PSU design effects.
3) The observations of unemployment design effect for Florida, Illinois, and New

York were too variable to support good t-tests.

Without direct estimates of within-PSU variance, I could not determine which of these factors caused the low power of the tests for Florida, Illinois, and New York.

For small or rural states, instability in the replication variance estimates caused high variability in unemployment design effects computed from these variance estimates. Since the analysis described above indicated that the bias in state unemployment standard error estimates computed by the current GVF method is reasonably low, the mean square error of unemployment standard errors computed using new state design effects (computed from the replicate weights) is likely to exceed that of standard error estimates computed by the current method. The BLS will therefore continue to use the current method to estimate standard errors for state unemployment totals.

Computing State Employment Design Effects

Since the confidence interval analysis described above indicated a downward bias in the employment standard error estimates computed by the current method, I used the replicate weights to estimate employment design effects for all states. Except for the states in Table 1, the estimated CV's of these design effects ranged from twenty-five to fifty percent. In order to gain stability in the state employment design effects, I grouped similar states together and computed a within-PSU design effect for each group, thus incurring some bias. I adopted a "linear programming" approach to collapsing states for computing employment design effects:

1. For a given state *S*, form all possible groups of states *G* such that:

   a) *G* includes *S*.
   b) *G* comprises two to five contiguous states.
   c) The number of states in *G* bordering *S* equals or exceeds the number of states in *G* not bordering *S*.

2. Choose the group *G* which maximizes $O_S = n_S/n_G$, where

   n_S = sample size for state *S*, and
   n_G = sample size for group *G*,

   subject to the following constraints:

   a) $CV(var_G) \leq 35\%$, where var_G is a *monthly* variance estimate from group *G*;
   b) $CV(de_G) \leq 20\%$, where de_G is the *average* employment design effect for March through December for group *G*; and
   c) $de_S - \hat{\sigma}_{de} \leq de_G \leq de_S + \hat{\sigma}_{de}$, where
   de_S = estimated design effect for state *S*;
   $\hat{\sigma}_{de}$ = standard error of de_S, estimated from the ten monthly observations.

The idea that states within the groups should be contiguous is based on the belief that employment design effect is correlated with some economic and demographic characteristics. Though the bias due to collapsing states cannot be estimated, use of O_S above as an "objective function" is intended to minimize it: O_S is clearly negatively correlated with this bias. Constraint (c) serves as a bias control, while constraints (a) and (b) ensure a minimum level of reliability for the design effects. The upper bounds on the CV's of monthly variance estimates and average design effects are based on feasibility, in view of the corresponding CV's for the eleven large states. Table 4 gives the new design effects, for selected states, computed using this approach.

Summary and Conclusions

To estimate variances for CPS labor force estimates, the Census Bureau developed a variance estimation system using Dr. Robert Fay's method of generalized replication. Since the CPS employs a one-PSU-per-stratum sample design, Census created a two- or three-PSU-per-stratum "pseudo-design" in order to apply the replication method. At the request of BLS, Census made the 1987 replicate weights available in a public data set. Users may easily compute variance and covariance estimates from these weights.

Using the replicate weights, I evaluated the variance estimation method the BLS uses for state employment and unemployment totals. I found that the current BLS method yielded good estimates of variance for unemployment totals and low estimates of variance for employment totals. I computed new state employment design effects from the 1987 replicate weights. Using these new design effects, the BLS may now compute less biased standard error estimates for state employment totals.

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Table 1
STATES IN ASCENDING ORDER OF %CV ON VARIANCE ESTIMATES

	Number of SECU's	Degrees of Freedom	%CV (var)
California	93	47	20.96
Massachusetts	50	47	21.17
New Jersey	52	47	21.41
Pennsylvania	53	47	21.60
New York	84	47	21.76
Florida	60	47	21.86
Michigan	51	45	22.09
North Carolina	49	42	22.91
Ohio	47	40	23.57
Texas	48	38	24.32
Illinois	42	36	24.83

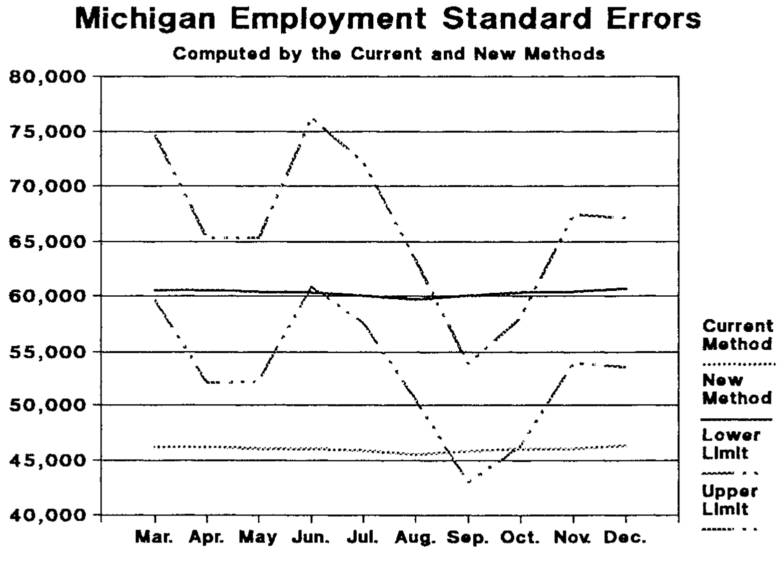

Figure 1

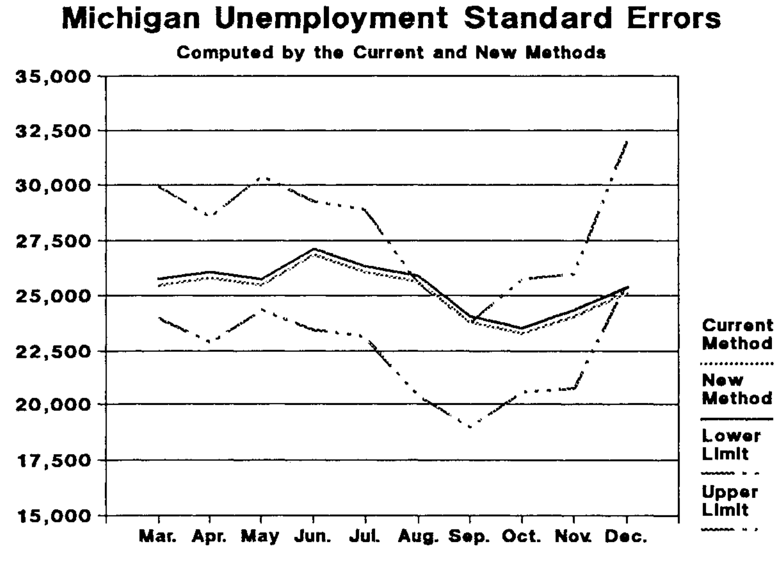

Figure 2

Table 2
UNEMPLOYMENT DESIGN EFFECTS and T-Statistics for Nine Large States

	Average Design Effect	Standard Error	T Statistic	p-value
California	1.264	0.259	-0.066	0.949
Florida	1.423	0.338	1.361	0.211
Illinois	1.418	0.318	1.355	0.209
Massachusetts	1.150	0.212	-1.781	0.109
Michigan	1.297	0.198	0.441	0.670
New Jersey	1.169	0.229	-1.385	0.199
New York	1.378	0.369	0.937	0.373
North Carolina	1.338	0.335	0.769	0.462
Pennsylvania	1.283	0.281	0.304	0.768

Table 3
POWER OF T-TESTS Under Three Simple Alternatives

	Power 1	Power 2	Power 3
California	0.26	0.73	0.98
Florida	0.04	0.16	0.50
Illinois	0.03	0.17	0.58
Massachusetts	0.03	0.42	0.94
Michigan	0.28	0.88	0.99
New Jersey	0.05	0.50	0.93
New York	0.03	0.18	0.53
North Carolina	0.04	0.30	0.68
Pennsylvania	0.16	0.60	0.93

Table 4
Optimal State Collapsing Patterns for Computing Employment Design Effects

State	Collapsed with	Within-PSU Employment Design Effect	Value of Objective Function O_s	CV of Monthly Variance Estimates	CV of Average Design Effect
Alabama	Mississippi Tennessee	1.287	0.329	0.300	0.165
Arizona	New Mexico Oklahoma	1.301	0.305	0.291	0.159
Arkansas	Oklahoma New Mexico	1.213	0.355	0.279	0.196
Colorado	Arizona New Mexico Utah	1.592	0.256	0.347	0.195
Idaho	Nevada Wyoming	1.060	0.401	0.319	0.199
Iowa	Missouri Minnesota Tennessee	1.273	0.252	0.270	0.154
Indiana	Kentucky Missouri	1.365	0.381	0.265	0.184
Kansas	Oklahoma	1.326	0.510	0.330	0.166
Mississippi	Alabama Tennessee	1.287	0.344	0.300	0.165
Missouri	Iowa	1.562	0.530	0.296	0.187
Nebraska	Iowa	1.048	0.506	0.329	0.170
New Hampshire	Vermont	1.542	0.482	0.316	0.200
North Dakota	Montana South Dakota Wyoming	1.569	0.268	0.273	0.186
Oklahoma	Kansas	1.326	0.490	0.330	0.166
Utah	Nevada Wyoming	1.250	0.363	0.302	0.173
Vermont	New Hampshire	1.542	0.518	0.316	0.200