Methodology for Variance of Change Estimates
For State-Level 1999 and 2000 Poverty Rates for Children Under 18

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1 Background

The Department of Health and Human Services (HHS) asked the U.S. Census Bureau's Small Area Estimates Branch to provide them with model-based estimates of child poverty on an annual basis to assist in determining which states had a greater than 5 percent poverty rate increase between two consecutive income years. This paper addresses the change between income years 1999 and 2000. The data provided to HHS help identify states for which the following equivalent statements are true:

$$\frac{\text{(Poverty Rate 2000) - (Poverty Rate 1999)}}{\text{Poverty Rate 1999}} > .05.$$

$$\text{(Poverty Rate 2000) - (Poverty Rate 1999)} > .05\times\text{(Poverty Rate 1999)}.$$

$$\text{(Poverty Rate 2000) - }1.05\times\text{(Poverty Rate 1999)} > 0.0.$$

This document discusses the derivation of the following estimates and test statistics provided to HHS:

- Variance of (Poverty Rate 2000 - Poverty Rate 1999) for children ages 0 - 17.
- Variance of (Poverty Rate 2000 - 1.05 $\times$ (Poverty Rate 1999)) for children ages 0 - 17.
- z-statistics for the test of the null hypothesis that poverty for children ages 0 - 17 has not increased by more than 5 percent.

The poverty estimates used in this analysis are from the Small Area Income and Poverty Estimates (SAIPE) program. SAIPE produces model-based estimates of official poverty as measured by the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC). Complete documentation of all methods used to produce the 1999 and 2000 poverty estimates is available on the SAIPE web site, http://www.census.gov/hhes/www/saipe.html.

For the remainder of this document "change estimate" refers to the 2000 poverty rate for children ages 0-17 minus the 1999 poverty rate for children ages 0-17; while "change variance estimate" is the variance of this quantity. "1.05 change estimate" refers to the 2000 poverty rate for children ages 0-17 minus 1.05 times the 1999 poverty rate for children ages 0-17; while "1.05 change variance estimate" is the variance of this quantity.

The results of the hypothesis tests performed will be presented in Section 2. A complete listing of these results can be found in Table 1 and Table 2 located at the end of this document. In Section 3 we will discuss the mathematical details of the change variance estimation and 1.05

[1] Formula (1) has been clarified. See page 7 for details.

change variance estimation. We outline specific details about estimation of parameters needed to produce these variance estimates in Section 4.

2 Results

The change variance estimate can be used, in conjunction with the change estimate, to test whether there is statistically significant evidence that the poverty rate increased. The 1.05 change variance estimate, in conjunction with the 1.05 change estimate, can be used to test whether there is statistically significant evidence that the poverty rate has increased by more than 5 percent. To test for statistically significant evidence that the poverty rate has increased by more than 5 percent, z-statistics were created for the one-tailed hypothesis test detailed as follows:

Null Hypothesis: Poverty has not increased by more than 5 percent.

$$(2000\ \text{Poverty Rate})\ -\ 1.05 \times (1999\ \text{Poverty Rate}) \leq 0\,.$$

Alternative Hypothesis: Poverty has increased by more than 5 percent.

$$(2000\ \text{Poverty Rate})\ -\ 1.05 \times (1999\ \text{Poverty Rate}) > 0\,.$$

Test Statistic:

$$z = \frac{((2000\ \text{Poverty Rate})\ -\ 1.05 \times (1999\ \text{Poverty Rate}))}{\sqrt{\text{Var}((2000\ \text{Poverty Rate})\ -\ 1.05 \times (1999\ \text{Poverty Rate}))}}\,.$$

z has a standard normal distribution when poverty has increased by exactly 5 percent.

There are two ways to perform this test. One way is to apply this test separately to each state. A problem with this approach is that if no state had an increase greater than 5 percent and we performed this test separately for each state, then the probability that we would conclude one or more states had an increase greater than 5 percent may be larger than the stated significance level. This problem is referred to as the problem of “multiple comparisons”. The second way to perform the test is the Bonferroni approach. The Bonferroni approach addresses the problem of multiple comparisons by using a critical value such that, if the null hypotheses are true for all of a set of tests, the probability that any one of these tests yields a significant result is no larger than a specified significance level.

For our tests we use a 10 percent significance level. For a set of 51 tests with the standard normal z-statistic, the Bonferroni 10 percent one-tailed critical value is 2.88. Any state with a z-statistic greater than 2.88 is considered to have a poverty rate increase greater than 5 percent. No states have z-statistics greater than 2.88 when comparing 1999 and 2000 poverty rates. *Thus, using this test we do not find statistical evidence that any state had a 0-17 poverty rate increase greater than 5 percent between 1999 and 2000.*

As described, the Bonferroni approach is appropriate for answering the question, "Is there evidence that any state had a poverty rate increase exceeding 5 percent?" A different critical value would be appropriate to test for evidence of a poverty rate increase greater than 5 percent in a particular state that was selected in advance, that is, the state was not selected based on looking at the results for all the states. This critical value is 1.28, the cutoff for the one-tailed test with significance level of 10 percent. This is an appropriate procedure for individual states to use in examining their own results. If a given state selected in advance has a z-statistic greater than 1.28 one may conclude it had a poverty rate increase greater than 5 percent. No state has a z-statistic greater than 1.28. Therefore, even if we ignore multiple comparison issues and do separate 10 percent tests for each state, no state would show a significant increase of more than 5 percent.

The results for each state are located in Table 1 and Table 2. Table 1 contains the point estimates and Table 2 contains the standard errors and z-statistics. For general interest, results for the change variance estimates are also provided. These can be used to test for evidence of any increase in the poverty rate. The critical value of 2.88 should be used when looking for evidence that any state had a poverty rate increase, and 1.28 should be used by individual states examining their results separately and independently.

3 Mathematical Details

The state poverty model used is as follows:

$$y_i = Y_i + e_i \qquad e_i \sim N(0, V_{ei})$$
$$Y_i = X_i\beta_i + u_i \quad u_i \sim N(0, \sigma_{ui}^2 I)$$

where

y_i = vector of 51 state CPS ASEC estimates of poverty ratios for a given age group and a given year,

Y_i = vector of "true" poverty ratios for given age group and given year,

X_i = matrix of predictor variables for given age group and given year; β_i are the corresponding regression parameters,

u_i = vector of model errors for a given age group and given year assumed independent across states; σ_{ui}^2 is their common variance,

e_i = vector of sampling errors for a given age group and given year assumed independent across states; V_{ei} is the diagonal matrix giving the sampling error variances for each state for the given age group and given year.

The subscript i = 1, 2, 3, 4 indexes the four CPS equations for the two years (1999 and 2000) and two age groups (0 - 4 and 5 - 17) according to the following scheme:

i = 1: y_1 = 1999 CPS estimated poverty ratio for children 0 - 4
i = 2: y_2 = 1999 CPS estimated poverty ratio for children 5 - 17
i = 3: y_3 = 2000 CPS estimated poverty ratio for children 0 - 4
i = 4: y_4 = 2000 CPS estimated poverty ratio for children 5 - 17.

Starting with income year 2000, the CPS ASEC estimates are obtained from a significant expansion of the previous March income supplement sample. The expanded sample is referred to as the SCHIP sample expansion because it was designed to improve the statistical reliability of certain estimates used in the funding formula for the State Children's Health Insurance Program. The distinction between the estimates from the SCHIP sample and the traditional March supplement estimates is most important for the discussion in Section 4 of how we estimated sampling error variances (the V_{ei}) and sampling error correlations. Given the V_{ei} and the other data (y_i and X_i), the above model can generally be estimated in the same fashion for any year. One qualification to this is that since 1999 is also the year for which Census 2000 provided poverty estimates (though not official poverty estimates), this year was given special treatment in the model estimation. This special treatment (use of an informative prior distribution for the regression parameters β_i) is also discussed in Section 4.

We model poverty ratios for children age 0-4 and children age 5-17 separately.[2] The poverty ratios are defined as CPS estimated number in poverty 0-4 divided by CPS estimated population 0-4, and CPS estimated number in poverty 5-17 divided by CPS estimated population 5-17, respectively. Poverty ratios differ from poverty rates wherein the denominator would be the CPS estimated poverty universe. The poverty universe excludes people in military barracks, institutional group quarters, and unrelated individuals under age 15. (For further discussion of poverty measurement, see http://www.census.gov/hhes/poverty/povdef.html, and for further discussion of CPS concepts and definitions, see http://www.census.gov/population/www/cps/cpsdef.html.) We use CPS weighted estimates in both the denominators and numerators because their positive correlation with each other reduces the variance of the resulting poverty ratios. We model poverty ratios instead of poverty rates because their construction is more straightforward and more reliable. (For a discussion of denominators for poverty rates see the SAIPE web site at http://www.census.gov/hhes/www/saipe/techdoc/inputs/denom.html.) We convert model-based estimates of poverty ratios for children 0-4 and children 5-17 into poverty rates for children 0-17 by the following steps:

- First, for each state we compute the model-based estimates of the true poverty ratios for children ages 0-4 and children ages 5-17 for each year (see SAIPE web site).
- We then get the estimated numbers in poverty in the two age groups by multiplying the model-based estimates of the poverty ratios by corresponding demographic population estimates.[3] The demographic population estimates are available from the

[2] This is to assist HHS in its Head Start planning.
[3] This is true except for a decennial census year where we use the decennial census population counts. Thus, for income year 1999 we used the Census 2000 population counts.

U.S. Census Bureau's population estimates program and we adjust them to represent the population covered by the CPS.

- The estimated number in poverty for each state is multiplied by a raking factor (defined below) for each combination (*i*) of age group and year so that the resulting estimated state numbers in poverty sum to the CPS national estimate for that combination of age group and year.[4]
- For each state we then add the raked number in poverty 0-4 to the raked number in poverty 5-17 to get the estimated number in poverty 0-17, for a given year.
- Finally, we form the estimated poverty rates for children ages 0-17 by dividing the estimated numbers in poverty 0-17 by the demographic poverty universe estimates for children 0-17 (poverty universe for children 0-4 plus poverty universe for children 5-17).

Note that in the second step we multiply the estimated poverty ratios by the demographic estimates of population rather than by CPS estimates of population. The demographic estimates of population have no sampling error and, though they contain other (nonsampling) errors, are considered to be more accurate than population estimates constructed from CPS data. The demographic population estimates are thus more appropriate for multiplying the estimated poverty ratios than are CPS estimates of population, while the latter are more suitable as denominators of the poverty ratios (for the reason noted above).

We let

$N_{1k} =$ 2000 demographic population estimate for children under 5 in state k,

$N_{2k} =$ 2000 demographic population estimate for children 5 - 17 in state k,

$N_{3k} =$ 2001 demographic population estimate for children under 5 in state k,

$N_{4k} =$ 2001 demographic population estimate for children 5 - 17 in state k,

and denote

$U_{1k} =$ 2000 demographic poverty universe estimate for children under 5 in state k,

$U_{2k} =$ 2000 demographic poverty universe estimate for children 5 - 17 in state k,

$U_{3k} =$ 2001 demographic poverty universe estimate for children under 5 in state k,

[4] Note that the scaling factors applied to the 1999 model-based poverty ratio estimates use population estimates for 2000, and the scaling factors for 2000 use population estimates for 2001. This is because the CPS estimates that we model use data from interviews conducted in February, March, and April of a given year (the survey year) with income reported the previous year (the income year, IY). The relevant population estimates to apply to the poverty ratio estimates are those for the survey year, which is 2000 for IY 1999 poverty estimates and 2001 for IY 2000 poverty estimates.

U_{4k} = 2001 demographic poverty universe estimate for children 5 - 17 in state k.

We define the scaling factors for the two age groups in each year as

$$r_{1k} = \frac{N_{1k}}{U_{1k} + U_{2k}}\ , \quad r_{2k} = \frac{N_{2k}}{U_{1k} + U_{2k}}$$

$$r_{3k} = \frac{N_{3k}}{U_{3k} + U_{4k}}, \quad r_{4k} = \frac{N_{4k}}{U_{3k} + U_{4k}}$$

and we define the raking factor for each combination (i) of age group and year as

$$RF_i = \frac{\text{CPS direct national estimate of number in poverty for age group - year combination } i}{\sum_k (\text{model - based estimate of number in poverty for state } k \text{ for age group - year combination } i)}.$$

Letting R_i be a diagonal matrix with the r_{ik} terms on the diagonal, the error in the change estimate can be written as follows:

$$[R_3(Y_3 - RF_3\hat{Y}_3) + R_4(Y_4 - RF_4\hat{Y}_4)] - [R_1(Y_1 - RF_1\hat{Y}_1) + R_2(Y_2 - RF_2\hat{Y}_2)]$$

where $Y_i - RF_i\hat{Y}_i$ is the error in the model-based poverty ratio estimate $\hat{Y}_i$ for combination (i) of age group and year. The diagonal of the variance matrix of this expression will be the change variance estimates. Similarly, the error in the 1.05 change estimate can be written as

$$[R_3(Y_3 - RF_3\hat{Y}_3) + R_4(Y_4 - RF_4\hat{Y}_4)) - 1.05[R_1(Y_1 - RF_1\hat{Y}_1) + R_2(Y_2 - RF_2\hat{Y}_2)],$$

and the diagonal of the variance matrix of this expression will be the 1.05 change variance estimates.

Bell (1999, 2001) determined that the vector of prediction errors for combination (i) of age group and year can be expressed as

$$Y_i - RF_i\hat{Y}_i = A_i \cdot u_i + (A_i - I) \cdot e_i + A_i X_i \beta_i$$

where

$$A_i = (1 - RF_i)I + RF_i(I - H_i)(I - M_i),$$

$$H_i = \sigma_{ui}^2 \Sigma_i^{-1}, \quad \Sigma_i = \sigma_{ui}^2 I + V_{ei}, \quad \text{and } M_i = X_i(X_i' \Sigma_i^{-1} X_i)^{-1} X_i' \Sigma_i^{-1}.$$

The term $A_i X_i \beta_i$ can be rewritten as $(1 - RF_i) \times X_i \beta_i$. This is fundamentally a bias term that arises from the raking under the model assumption that the regression function $X_i \beta_i$ produces unbiased estimates. (The raking factor RF_i also includes some random estimation error.) The model is, of course, an approximation, and the raking is done because it is believed to reduce possible bias arising from failure of the model assumptions. We therefore ignore this bias term in computing measures of error for the raked estimates, and just compute the covariance matrix of the contribution to the error of the first two terms, $A_i \cdot u_i + (A_i - I) \cdot e_i$.

Proceeding with the assumption that the term $A_i X_i \beta_i$ can be ignored, the errors in the change estimate and the 1.05 change estimate can both be expressed as

$$R_3[A_3 \cdot u_3 + (A_3 - I) \cdot e_3] + R_4[A_4 \cdot u_4 + (A_4 - I) \cdot e_4]$$
$$+ \tilde{R}_1[A_1 \cdot u_1 + (A_1 - I) \cdot e_1] + \tilde{R}_2[A_2 \cdot u_2 + (A_2 - I) \cdot e_2]$$

where $\tilde{R}_1$ and $\tilde{R}_2$ are $-R_1$ and $-R_2$ for the error in the change estimate, and they are $-1.05R_1$ and $-1.05R_2$ for the error in the 1.05 change estimate. The covariance matrix of the above expression can be written as [5]

$$\sum_i \sum_j [\overline{R}_i \cdot (A_i - I)]Cov(e_i, e_j)[\overline{R}_j \cdot (A_j - I)]' + \sum_i \sum_j [\overline{R}_i \cdot A_i]Cov(u_i, u_j)[\overline{R}_j \cdot A_j]', \quad (1)$$

where, for the 1.05 change variance estimates:

$\overline{R}_i = -1.05R_i$ when i = 1 or 2, and $\overline{R}_i = R_i$ when i = 3 or 4,

and, for the change variance estimates:

$\overline{R}_i = -R_i$ when i = 1 or 2, and $\overline{R}_i = R_i$ when i = 3 or 4.

Note that we assume the sampling errors and model errors are uncorrelated across states and uncorrelated with each other. Therefore $Cov(e_i, e_j)$ and $Cov(u_i, u_j)$ are diagonal matrices. There are 32 terms all together in this sum.

4 Parameter Estimation

To estimate equation (1) we must estimate the individual variances and correlations (parameters) appearing in this expression. We do this in three ways:

- by estimating models for sampling error in the CPS state estimates using direct estimates of the CPS sampling error variances and covariances;
- by averaging direct estimates of certain sampling error correlations not covered by the sampling error models; and

[5] The assignments for *R* shown in formula (1) differ from the assignments shown in the 3/29/04 posting of this document. In the previous version, the assignments for *R* had been shown as positive for all *i*, when in fact the assignments are negative when *i* = 1, 2. Computations for posted results have always used the correct assignments for *R* as given above.

- by estimating the models for the state CPS estimates that are used to produce the state poverty ratio predictions.

Below we discuss our use of these three approaches in more detail. In doing so we sometimes need to distinguish when we used data from the traditional CPS ASEC (traditional sample) and when we used data from the SCHIP sample.

We estimated the variances V_{ei} for each age-group poverty ratio (0-4 and 5-17) by fitting sampling error models to directly estimated CPS sampling error covariance matrices for each state. Elizabeth Huang and Bob Fay produced the latter using the VPLEX program, as described in Fay and Train (1995). Otto and Bell (1995) discuss the type of sampling error models used. Separately for each age-group poverty ratio, we fit the sampling error models to the directly estimated state covariance matrices by maximum likelihood assuming a Wishart distribution for the covariance matrices. The models allow the sampling variances (nonzero elements of the diagonal matrices V_{ei}) to differ across states and years through a generalized variance function that depends on the poverty ratio estimates and on the CPS state sample size (which is significantly larger for the SCHIP sample than for the traditional ASEC sample). The models assume, however, that sampling error correlations between years (ρ_{e13} and ρ_{e24}) are constant across states for a given poverty ratio. The models also assume stationarity of the correlations, which implies that sampling error correlations for a given age group poverty ratio between two years t and j depend only on the absolute lag $|t - j|$. Because we use separate sampling error models for each age-group poverty ratio, the fitted sampling error models do not provide estimates of sampling error correlations between the poverty ratios for different age groups.

Sampling error covariance matrices were produced for 1995-2000 for estimates from the traditional sample and for 2000-2001 for estimates from the SCHIP sample. (For 2000 both traditional and SCHIP estimates were available.) Because we believed that the properties of the sampling errors in the SCHIP estimates could differ from those in the traditional estimates (beyond simple effects that would be accounted for in the models by the increase in sample size), we fit separate sampling error models for the traditional and SCHIP estimates using their two different sets of covariance matrices. Since we only had two years of variances and covariances for the SCHIP estimates we simplified the sampling error model slightly for the SCHIP estimates (dropping the random effects discussed in Otto and Bell (1995)).

We estimated sampling error correlations between the poverty ratios (ρ_{e13}, ρ_{e24}, $\rho_{e12} = \rho_{e34}$, ρ_{e14}, ρ_{e23}) by averaging the corresponding direct estimates over states and years. Basically, we constructed correlation matrices from the direct sampling covariance matrices discussed above, and then averaged these over the 51 "states" (including D.C.). We then assumed stationarity of the sampling error correlations between different poverty ratios, meaning that for two years t and j the correlation depends only on the lag $t - j$. Given this assumption we averaged over years the state average correlations just obtained that corresponded to the same two poverty ratios and a common lag. The stationarity assumption implies that $\rho_{e12} = \rho_{e34}$, since these are both sampling error correlations between the 0-4 and 5-17 poverty ratios within a single year at lag 0. So in estimating this correlation, our approach took the directly estimated sampling error correlations between the 0-4 and 5-17 poverty ratios for each year 1995-2001, and averaged these over all the states and all seven years. We used analogous averaging procedures to estimate ρ_{e13}, ρ_{e24}, ρ_{e14} and ρ_{e23}. In all cases we used simple unweighted averages of the correlations for this estimation. Note that we averaged the correlations over all years not distinguishing between the traditional and SCHIP samples, effectively assuming that the correlations in question remain unchanged with the SCHIP sample expansion. Previously we had experimented some with averages that used weights proportional to state population size, but this had little effect on the results.

We estimated the σ^2_{ui} in fitting the SAIPE state models to the CPS direct poverty ratio estimates. We used a Bayesian approach to estimation of the state model, and we can regard σ^2_{ui} as estimated by its posterior mean. Ordinarily we use a noninformative (flat) prior for all the model parameters. For income year 1999, however, we used a mildly informative (proper) prior for some of the regression parameters, though still keeping a flat prior on the variance. The informative prior was used because 1999 is also the year to which the Census 2000 poverty estimates refer, and so we had reason to expect that for this year the regression parameters on the predictor variables other than the decennial census data would be close to zero. We also had empirical evidence of this from previous model fits for income year 1989. Analysis leading to this decision is discussed in Huang and Bell (2002) and the prior used is discussed at http://www.census.gov/hhes/www/saipe/techdoc/1999/99statemod.html. The informative prior pulled the estimates of the regression coefficients involved towards zero. It also resulted in slightly smaller estimates of σ^2_{ui} than were obtained with a flat prior on all parameters, and this produced slightly smaller prediction error variances for the model estimates. Though we did not compute change estimate variances under the completely flat prior, the change estimate variances should also be slightly smaller with the informative prior. This, in turn, would tend to produce test statistics (as discussed in Section 2) slightly larger in magnitude, though the changes in the estimates of the regression coefficients due to the informative prior would also affect the test statistics.

We estimated correlations of the model errors (ρ_{u12}, ρ_{u13}, ρ_{u14}, ρ_{u23}, ρ_{u24}, ρ_{u34}) by using the Bayesian approach to treat each pair of CPS state equations jointly. For each of the six distinct possible pairs of the four equations for the 1999 and 2000 CPS equations for the 0-4 and 5-17 poverty ratios, we specified prior distributions for the regression coefficients and the model variances as just discussed. The prior for the model error correlation involved was taken to be uniform on the interval [-1,1]. We then took the posterior mean of the model error correlation as its point estimate. Note that although this model fitting produced new estimates of the other model parameters involved in each pair of equations (the regression parameters and model error variances), for calculation of the change estimate variances we left these other model parameters at their original Bayesian estimates obtained from fitting the single CPS equations separately. This was done so that results would remain consistent with the production state model-based estimates, which involved fitting only one CPS state equation at a time. The calculations required for this joint Bayesian treatment of two CPS equations were done using the WinBUGS package (Spiegehalter, et al. 1996).

References:

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Table 1. Point Estimates for Children Ages 0-17

State	1999 Poverty Rate	2000 Poverty Rate	Percent[1] Change	Change[2] Estimate	1.05 Change[3] Estimate
Alabama	22.2	20.5	-7.7	-1.7	-2.8
Alaska	11.2	11.5	2.7	.3	-.3
Arizona	18.8	18.7	-.5	-.1	-1.0
Arkansas	21.8	21.8	0	0	-1.1
California	20.2	18.5	-8.4	-1.7	-2.7
Colorado	12.0	12.2	1.7	.2	-.4
Connecticut	10.2	10.1	-1.0	-.1	-.6
Delaware	14.0	12.6	-10.0	-1.4	-2.1
District of Columbia	29.2	26.4	-9.6	-2.8	-4.3
Florida	18.5	17.7	-4.3	-.8	-1.7
Georgia	18.3	17.5	-4.4	-.8	-1.7
Hawaii	14.5	14.3	-1.4	-.2	-.9
Idaho	16.8	15.2	-9.5	-1.6	-2.4
Illinois	15.0	14.6	-2.7	-.4	-1.2
Indiana	11.6	12.1	4.3	.5	-.1
Iowa	11.0	10.8	-1.8	-.2	-.8
Kansas	14.3	11.9	-16.8	-2.4	-3.1
Kentucky	20.2	19.3	-4.5	-.9	-1.9
Louisiana	26.4	24.4	-7.6	-2.0	-3.3
Maine	14.8	12.9	-12.8	-1.9	-2.6
Maryland	10.1	10.7	5.9	.6	.1
Massachusetts	15.0	11.5	-23.3	-3.5	-4.3
Michigan	14.2	13.7	-3.5	-.5	-1.2
Minnesota	9.3	8.7	-6.5	-.6	-1.1
Mississippi	26.1	24.9	-4.6	-1.2	-2.5
Missouri	16.7	14.8	-11.4	-1.9	-2.7
Montana	20.2	18.8	-6.9	-1.4	-2.4
Nebraska	12.5	11.9	-4.8	-.6	-1.2
Nevada	15.3	13.6	-11.1	-1.7	-2.5
New Hampshire	8.2	6.9	-15.9	-1.3	-1.7
New Jersey	10.9	10.5	-3.7	-.4	-.9
New Mexico	26.4	25.5	-3.4	-.9	-2.2
New York	21.0	19.1	-9.0	-1.9	-2.9
North Carolina	17.3	16.5	-4.6	-.8	-1.7
North Dakota	15.6	13.1	-16.0	-2.5	-3.3
Ohio	16.0	14.1	-11.9	-1.9	-2.7
Oklahoma	19.7	20.0	1.5	.3	-.7
Oregon	15.7	15.1	-3.8	-.6	-1.4
Pennsylvania	14.0	13.1	-6.4	-.9	-1.6
Rhode Island	16.2	15.0	-7.4	-1.2	-2.0
South Carolina	19.2	18.2	-5.2	-1.0	-2.0
South Dakota	15.4	15.1	-1.9	-.3	-1.1
Tennessee	18.1	17.8	-1.7	-.3	-1.2
Texas	21.8	20.7	-5.0	-1.1	-2.2
Utah	10.0	11.1	11.0	1.1	.6
Vermont	12.3	11.6	-5.7	-.7	-1.3
Virginia	12.4	12.2	-1.6	-.2	-.8
Washington	13.1	13.2	.8	.1	-.6
West Virginia	23.8	21.9	-8.0	-1.9	-3.1
Wisconsin	10.9	11.0	.9	.1	-.4
Wyoming	15.1	13.9	-7.9	-1.2	-2.0

[1] 100 × [(2000 Poverty Rate – 1999 Poverty Rate)/(1999 Poverty Rate)]
[2] 2000 Poverty Rate – 1999 Poverty Rate
[3] 2000 Poverty Rate – 1.05 × (1999 Poverty Rate)
Source: U.S. Census Bureau, SAIPE estimates, http://www.census.gov/hhes/www/saipe.html.

Table 2. Standard Errors and z-statistics for Children Ages 0-17

State	Change[1] Estimate	S.E. of Change Est.	z-statistic[2]	1.05 Change[3] Estimate	S.E. of 1.05 Change Est.	z-statistic[4]
Alabama	-1.7	1.66	-1.01	-2.8	1.74	-1.60
Alaska	.3	1.56	.15	-.3	1.64	-.20
Arizona	-.1	1.70	-.07	-1.0	1.78	-.59
Arkansas	0	1.75	-.03	-1.1	1.83	-.63
California	-1.7	1.11	-1.53	-2.7	1.16	-2.34
Colorado	.2	1.52	.13	-.4	1.60	-.25
Connecticut	-.1	1.56	-.11	-.6	1.63	-.42
Delaware	-1.4	1.61	-.84	-2.1	1.69	-1.21
District of Columbia	-2.8	3.02	-.92	-4.3	3.14	-1.35
Florida	-.8	1.32	-.57	-1.7	1.38	-1.22
Georgia	-.8	1.60	-.51	-1.7	1.68	-1.03
Hawaii	-.2	1.62	-.08	-.9	1.70	-.50
Idaho	-1.6	1.59	-1.03	-2.4	1.66	-1.49
Illinois	-.4	1.22	-.34	-1.2	1.28	-.91
Indiana	.5	1.49	.35	-.1	1.57	-.04
Iowa	-.2	1.48	-.12	-.8	1.56	-.47
Kansas	-2.4	1.47	-1.65	-3.1	1.54	-2.04
Kentucky	-.9	1.61	-.56	-1.9	1.68	-1.14
Louisiana	-2.0	1.94	-1.01	-3.3	2.03	-1.62
Maine	-1.9	1.58	-1.20	-2.6	1.65	-1.59
Maryland	.6	1.54	.41	.1	1.62	.08
Massachusetts	-3.5	1.49	-2.36	-4.3	1.55	-2.75
Michigan	-.5	1.25	-.46	-1.2	1.30	-.98
Minnesota	-.6	1.49	-.44	-1.1	1.56	-.72
Mississippi	-1.2	2.01	-.62	-2.5	2.09	-1.22
Missouri	-1.9	1.52	-1.21	-2.7	1.59	-1.67
Montana	-1.4	1.75	-.77	-2.4	1.83	-1.29
Nebraska	-.6	1.52	-.42	-1.2	1.59	-.80
Nevada	-1.7	1.62	-1.01	-2.5	1.70	-1.42
New Hampshire	-1.3	1.61	-.83	-1.7	1.68	-1.04
New Jersey	-.4	1.30	-.25	-.9	1.35	-.64
New Mexico	-.9	2.00	-.44	-2.2	2.08	-1.06
New York	-1.9	1.24	-1.59	-2.9	1.29	-2.34
North Carolina	-.8	1.39	-.61	-1.7	1.46	-1.17
North Dakota	-2.5	1.60	-1.60	-3.3	1.68	-1.99
Ohio	-1.9	1.33	-1.49	-2.7	1.38	-2.01
Oklahoma	.3	1.72	.18	-.7	1.80	-.38
Oregon	-.6	1.59	-.40	-1.4	1.67	-.85
Pennsylvania	-.9	1.29	-.73	-1.6	1.35	-1.22
Rhode Island	-1.2	1.83	-.66	-2.0	1.92	-1.05
South Carolina	-1.0	1.59	-.60	-2.0	1.67	-1.14
South Dakota	-.3	1.79	-.12	-1.1	1.87	-.53
Tennessee	-.3	1.57	-.20	-1.2	1.64	-.75
Texas	-1.1	1.26	-.85	-2.2	1.31	-1.65
Utah	1.1	1.57	.70	.6	1.64	.36
Vermont	-.7	1.62	-.45	-1.3	1.70	-.79
Virginia	-.2	1.50	-.16	-.8	1.57	-.55
Washington	.1	1.51	.03	-.6	1.58	-.39
West Virginia	-1.9	1.84	-1.04	-3.1	1.92	-1.62
Wisconsin	.1	1.55	.06	-.4	1.63	-.28
Wyoming	-1.2	1.65	-.74	-2.0	1.73	-1.14

[1] 2000 Poverty Rate – 1999 Poverty Rate

[2] $((2000 \text{ Poverty Rate}) - (1999 \text{ Poverty Rate}))/\sqrt{\text{Var}((2000 \text{ Poverty Rate}) - (1999 \text{ Poverty Rate}))}$

[3] 2000 Poverty Rate – 1.05 × (1999 Poverty Rate)

[4] $((2000 \text{ Poverty Rate}) - 1.05\times(1999 \text{ Poverty Rate}))/\sqrt{\text{Var}((2000 \text{ Poverty Rate}) - 1.05\times(1999 \text{ Poverty Rate}))}$

See text for discussion of critical values.
Source: Author calculations.