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Calculating Coefficient of Variation for the Minimum Change School District Poverty Estimates and the Assessment of the Impact of Nongeocoded Tax Returns

Jerry Maples

Statistical Research Division
U.S. Census Bureau
Washington, D.C. 20233

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Jerry Maples
Bureau of the Census

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1 Introduction

In this paper, we propose a method that can be used in intercensal years to calculate the coefficient of variation (CV) for the Minimum Change method estimates of the number of children in poverty for school districts used in the Small Area Income and Poverty Estimates (SAIPE) program at the U.S. Census Bureau. The Small Area Income and Poverty Estimates program provides estimates for selected income and poverty statistics for states, counties and school districts. The Minimum Change methodology, outlined in Maples and Bell (2007), incorporates current IRS income tax data about sub-county-level poverty for school-age children. These estimates are used in the administration of federal programs and the allocation of federal funds to local areas. Additionally, we will attempt to empirically quantify the possible improvement in CV that might be made by improving the geocoding process (assigning the address of an income tax return to a census block) to reduce the percentage of nongeocoded exemptions. Comparisons of CVs using appropriate year IRS income tax data for school district poverty will be made against CVs using only the Census long-form CVs from 2000 and 1990. The Minimum Change method will use Census 2000 as the "previous census" when estimating poverty in 1990.

School district estimates for the number of poor children are the sum of their school district piece estimates. School districts that cross county lines are split into pieces that correspond to the intersection of county and school district. Making estimates at the level of a school district piece rather than as whole school district allows for a simpler method of controling the number of poor school-age children to the county level estimates to maintain consistency between different geographical levels.

2 The Minimum Change Method School District Piece Estimator

In 2007, the SAIPE program changed the school district estimator to include information from the IRS income tax data. The production estimator for school district piece j in county i has the form:

$$y_{ij} = \frac{\text{taxpoorshare}_{ij}\text{cpoor}_i}{\text{taxchildshare}_{ij}\text{cpop}_i}\ \ \text{sdpop}_{ij}$$

where

- taxpoorshare_{ij} is the Minimum Change share of the poor child tax exemptions
- $\text{taxchildshare}_{ij}$ is the Minimum Change share of all child tax exemptions
- cpoor_i is the SAIPE county model estimate of the number of related children in poverty 5-17
- cpop_i is the demographic county estimate of the number of related children ages 5-17
- sdpop_{ij} is the demographic estimate of the number of related children ages 5-17 in the school district piece

Consistency between the estimates at different geographic levels is important. Also, it is assumed that the estimates for a higher aggregation (county compared to subcounty piece) are more accurate. Therefore, the estimator y_{ij} is raked to agree with the county estimate. The form of the raked estimator is:

$$y^r_{ij} = \frac{\text{taxpoorshare}_{ij}\text{sdpop}_{ij}}{\text{taxchildshare}_{ij}}\frac{\text{cpoor}_i}{\text{cpop}_i} \times \frac{\text{cpoor}_i}{\sum_j \frac{\text{taxpoorshare}_{ij}\text{sdpop}_{ij}}{\text{taxchildshare}_{ij}}\frac{\text{cpoor}_i}{\text{cpop}_i}}$$

$$= \frac{\frac{\text{taxpoorshare}_{ij}\text{sdpop}_{ij}}{\text{taxchildshare}_{ij}}}{\sum_j \frac{\text{taxpoorshare}_{ij}\text{sdpop}_{ij}}{\text{taxchildshare}_{ij}}} \times \text{cpoor}_i = s_{ij}\text{cpoor}_i \qquad (1)$$

where s_{ij} is the estimated raked school district piece to county poverty share using the SAIPE production estimation procedure. If we assume that the share s_{ij} is independent of the county estimated number of poor children cpoor_i, then we can approximate a variance for y^r_{ij}:

$$Var(y^r_{ij}) \approx s^2_{ij}Var(\text{cpoor}_i) + \text{cpoor}^2_i Var(s_{ij}) \qquad (2)$$

Note that Eq(2) gives a Taylor expansion approximation of the variance for any estimate of the share that is uncorrelated with the county estimate.

The Minimum Change share (Maples and Bell 2007) uses the IRS income tax data where the data quality is good (as measured by the percent of tax exemptions able to be geocoded to census block geography) and moves towards the most recent census shares as the data quality in the IRS income tax data becomes less good.

The unraked estimator being used in production for the SAIPE program is similar to the POV-RT-MC-CEN estimator in Maples and Bell (2007). The POV-RT-MC-CEN estimator uses the Minimum Change algorithm on the IRS income tax data which are used to construct the poverty rate and the poverty rate is applied to a population estimate which is based on population shares from the most recent census. The slight difference is that the school district piece tax child poverty rate is used for the production estimator instead of the whole school district tax child poverty rate. Additionally, this form of the estimator allows for different (and better) population estimates for the school district piece.

2.1 Parameterization of $Var(s_{ij})$

Let c_{ij} be the census long-form estimate of the true school district piece to county poverty share, μ_{ij}. This estimate, which contains non-trivial sampling error variance, is the ratio of the estimated number of children in poverty in a school district piece to the corresponding estimated number of children in poverty in the county. The school district piece to county poverty share using the IRS income tax data also is an estimate of the true share, μ_{ij}. One major difference between these two estimates is that s_{ij} can estimate the share for any year with the appropriate IRS income tax data, while c_{ij} can only make estimates for census years. There are three pieces of information, s_{ij}, c_{ij} and $Var(c_{ij}) = Var(e_{ij})$ available to estimate $Var(s_{ij})$. For a census year (e.g. 1990 or 2000), suppose μ_{ij} is the true share, then:

$$s_{ij} = \mu_{ij} + \epsilon_{ij} \tag{3}$$

$$c_{ij} = \mu_{ij} + e_{ij} \tag{4}$$

where ϵ_{ij} is the error from the estimated share s_{ij} and e_{ij} is the survey error from the census long-form estimate, which we assume is unbiased ($E(e_{ij}) = 0$). It is also assumed that s_{ij} is an unbiased estimate of μ_{ij}. Equations (3) and (4) imply

$$\begin{aligned} s_{ij} - c_{ij} &= \epsilon_{ij} - e_{ij} \\ \Rightarrow E[(s_{ij} - c_{ij})^2] &= Var(\epsilon_{ij}) + Var(e_{ij}) \quad \text{assuming } \epsilon_{ij} \perp e_{ij} \\ \Rightarrow E[(s_{ij} - c_{ij})^2] - Var(e_{ij}) &= Var(\epsilon_{ij}) = Var(s_{ij}) \end{aligned} \tag{5}$$

How reasonable is the assumption of independence between ϵ_{ij} and e_{ij}? The census long-form estimator c_{ij} contains sampling error. The SAIPE estimator, s_{ij}, uses data from the previous census (not the current census which determines c_{ij}) and the IRS income tax data, thus the independence assumption seems reasonable. The assumption of unbiasness (or equivalently zero mean for ϵ_{ij}) can be relaxed, then instead of $Var(\epsilon)$ Equation (5) would estimate the mean squared error (MSE) which includes a bias squared term. Note that one could replace $Var(s_{ij})$ with the MSE of s_{ij} for the formulas and derivations below.

There are several possibilities to estimate $Var(s_{ij})$. First, we could assume that the expectation in (5) is constant, σ^2, for all school district piece shares. Maples and Bell (2007) show, however, that the precision of the share estimators are not constant but depend on population size and geocoding rates. One could assume that the variance of each share is different, $\widehat{Var}(s_{ij}) = (s_{ij} - c_{ij})^2 - \widehat{Var}(e_{ij})$; however, basing the estimate of the variance on a single point of data would make for a very noisy estimator. Since the shares are proportions, one could assume that the variance is proportional to $\mu_{ij}(1 - \mu_{ij})$. This gives a variance structure similar to a Beta distribution. We consider two structural assumptions for the variance of s_{ij}:

$$\text{Parameterization A:} \quad Var(s_{ij}) = \mu_{ij}(1 - \mu_{ij})\sigma^2_{ij} \tag{6}$$

$$\text{Parameterization B:} \quad Var(s_{ij}) = \mu_{ij}(1 - \mu_{ij})\sigma^2_{ij}/\text{cpop}_i \tag{7}$$

where σ^2_{ij} is the scalar effect to be estimated. Although we cannot estimate a unique σ^2_{ij} for every school district piece, the σ^2_{ij}'s can be split into k groups based on variables such as population size and geocoding rates such that the value of $\sigma^2_{ij} = \sigma^2_k$ is assumed to be constant within the group. We will substitute s_{ij} as a plug-in estimate for μ_{ij}. Parameterization B explicitly takes county size into account, whereas Parameterization A can only reflect differences in county size through the parameterization of σ^2_{ij}.

Note that the parameterizations of s_{ij} given above can be assumed for other estimates of the school district piece to county share, e.g. shares estimated using previous census long-form data. The validity of the estimated σ^2_k's depend on the parameterization being correct, which is very difficult to assess given the data available. However, comparisons of $\hat{\sigma}^2_k$ for alternative methods for estimating the shares (Minimum Change vs previous census share) still have some validity even if the parameterization is wrong. The validity of the comparisons hold because we are comparing averages of ϵ^2_{ij}.

3 Specification and Estimation of Variance Parameters

In the previous section, we gave two parametric forms for the variance of the within-county share of children in poverty. The unknown parameters σ^2_k, post-stratifying on county child population size and non-geocoding rate, will need to be estimated. The only datasets available to estimate the accuracy of the point estimates are the long-form data from the 1990 and 2000 censuses. An alternative specification for the σ^2_{ij}'s is to specify a parametric function of county child population size and non-geocoding rate for poor child tax exemptions.

Finding a suitable parametric form was problematic, and therefore the post-stratification approach was chosen.

The two variables that will be used to split the 3,141 counties and their 20,176 associated school district pieces into various groups are county population for 5-17 year olds and the non-geocoding rate (within county) of the poor child tax exemptions. The cutoffs for the various splits were made to ensure that a reasonable number of counties would fall into each group in both the 1990 and 2000 censuses. The categories for the population size are: <2500, 2500-10k, 10k-100k and 100k+. The categories for the poor child exemption non-geocoding rates are: 0%, 0-10%, 10-20%, 20-30%, 30-40% and 40+%. The numbers of school district pieces for the 1990 and 2000 cross classifications are given in Tables 1 and 2.

Some of the cells in Tables 1 and 2 are too small to adequately estimate a separate σ_k^2, and therefore some of the cells within size categories will be collapsed to ensure at least 100 school district pieces in each post-strata. Table 3 shows which cells are collapsed together. Note that the first row with 0% non-geocoding rate is a special case of counties that only contain one piece (the county and school district piece are identical/coterminous). These pieces have a share of 100% of the county with certainty, and the parameter σ_k^2 cannot be estimated given the parameterization.

3.1 Estimation of σ_k^2

The census long-form estimates for the school district piece to county share of children in poverty are measured with sampling error. We use the relation in Eq (5) to account for this source of variation so that we do not overestimate the σ_k^2's. To estimate the σ_k^2's for each of the twelve post-strata, we solve the following equations obtained by averaging (5) over school district pieces within post-stratum k, taking $n_k^{-1}\sum_{(i,j)\in k}(s_{ij}-c_{ij})^2$ as an estimator of $n_k^{-1}\sum_{(i,j)\in k}E(s_{ij}-c_{ij})^2$, where n_k is the number of school district pieces in post-stratum k and we substitute from (6) and (7) for $Var(s_{ij})$.

Parameterization A
$$\sum_{(i,j)\in k}[(s_{ij}-c_{ij})^2-\widehat{Var}(e_{ij})] = \sigma_{ak}^2\sum_{(i,j)\in k}s_{ij}(1-s_{ij})$$
$$\Rightarrow \hat{\sigma}_{Ak}^2 = \frac{\sum_{(i,j)\in k}\ (s_{ij}-c_{ij})^2-\widehat{Var}(e_{ij})}{\sum_{(i,j)\in k}\ s_{ij}(1-s_{ij})} \tag{8}$$

Parameterization B
$$\sum_{(i,j)\in k}[(s_{ij}-c_{ij})^2-\widehat{Var}(e_{ij})] = \sigma_{bk}^2\sum_{(i,j)\in k}s_{ij}(1-s_{ij})/\mathrm{cpop}_i$$
$$\Rightarrow \hat{\sigma}_{Bk}^2 = \frac{\sum_{(i,j)\in k}\ (s_{ij}-c_{ij})^2-\widehat{Var}(e_{ij})}{\sum_{(i,j)\in k}\ s_{ij}(1-s_{ij})/\mathrm{cpop}_i} \tag{9}$$

where the $\widehat{Var}(e_{ij})$'s are specified below. The main difference between parameterizations A and B is whether to explicitly take county population size into account or to have county size be averaged out in the post-strata.

For a county with J district pieces, let $x_{ij} \in (x_{i1}, ..., x_{iJ})$ be the census long-form counts for school district piece j with corresponding sampling variances $Var(x_{ij})$ for the number of children 5-17 in poverty. Let $x_{i+} = \sum_j x_{ij}$ be the census long-form county total of the number of children 5-17 in poverty. It is assumed that the census long-form sampling errors are independent between the school district pieces. The variance of the within-county shares from the census long-form can be approximated by the Delta method.

$$
\begin{aligned}
c_{ij} &= \frac{x_{ij}}{\sum_j x_{ij}} \\
Var(c_{ij}) &= Var(e_{ij}) \approx \sum_{j'=1}^{J} \left[\frac{\partial}{\partial x_{ij'}} \left(\frac{x_{ij}}{\sum_j x_{ij}} \right) \right]^2 \times Var(x_{ij'}) \\
&= \sum_{j' \neq j} \left(\frac{-x_{ij}}{x_{i+}^2} \right)^2 Var(x_{ij'}) + \left(\frac{1}{x_{i+}} + \frac{-x_{ij}}{x_{i+}^2} \right)^2 Var(x_{ij}) \\
\Rightarrow Var(e_{ij}) &\approx \frac{(x_{i+} - x_{ij})^2 Var(x_{ij}) + x_{ij}^2 \sum_{j' \neq j} Var(x_{ij'})}{x_{i+}^4} \qquad (10)
\end{aligned}
$$

We will make eight different sets of estimates for σ_k^2: two years (1990 and 2000) by two parameterizations (A and B) by two share estimators, Minimum Change and previous census share. That is, we first let s_{ij} be the Minimum Change estimator under (1) and compute the σ_k^2's. Next, we let s_{ij} be the previous census share estimator and compute a new set of σ_k^2's. The estimates of the σ_k^2's for the post-strata are given in Tables 4 (Parameterization A) and 5 (Parameterization B) for the Minimum Change Shares. Each table has the estimates from the 1990 and 2000 censuses and a combined estimate using sample size (from Tables 1 and 2) weighted average between the two censuses. Estimates of σ_k^2 using previous census shares are given in Tables 6 and 7. Table 8 compares the ratio of estimates of σ_k^2 from using the Minimum Change shares over using the previous census shares. The reductions in the estimates of σ_k^2 are very similar between the two parameterizations. Also, there is more reduction in the variance parameter as the county population size increases and as the non-geocoding rate decreases.

4 Comparing CVs for whole school district estimates

4.1 Creating CVs

Using the estimated σ_k^2's from Section 3.1 we can estimate the variance of s_{ij} and then estimate the variance of y_{ij} from (2). The variance of the estimated school district piece to county share s_{ij} is

- Parameterization A: $\widehat{Var}(s_{ij}) = s_{ij}(1 - s_{ij})\hat{\sigma}^2_{Ak}$
- Parameterization B: $\widehat{Var}(s_{ij}) = s_{ij}(1 - s_{ij})\hat{\sigma}^2_{Bk}/\text{cpop}_i$

The estimate of the number of children in poverty in a school district piece is assumed to be independent from the estimated number in school district pieces from other counties, and therefore the variance of the sum of the number of children in poverty for school district pieces (which are in different counties) is the sum of the variances:

$$\widehat{Var}(y^r_{sd}) = \widehat{Var}(\sum_{(i,j)\in sd} y^r_{ij}) = \sum_{(i,j)\in sd} \widehat{Var}(y^r_{ij}).$$

From the estimated variance for the number of related school age children in poverty, we can calculate the coefficient of variation, $CV = \sqrt{\widehat{Var}(y^r_{sd})}/y^r_{sd}$.

4.2 Comparisons of CVs

We will compare the CVs produced from the methodology detailed in Section 3 to the CVs from the direct estimates from the 1990 and 2000 census long-form surveys. Estimates of the CVs for both 1990 and 2000 used the weighted average version of the σ^2_k's (bottom third of Tables 5-7) as this would be the set of σ^2_k's to use for future years. The whole school districts are broken into groups defined by their population size (average size between 1990 and 2000). Whole school districts are used instead of school district pieces for this comparison because it is the whole school district estimates that are of interest.

Table 9 gives a comparison of the median CVs under the two parameterizations for the variance of the share. As expected, the CVs for both share based estimators are much higher than the CVs for the direct estimates using the long-form data. The CVs for the estimator using previous census shares are higher than the estimators using the Minimum Change shares with the exception of the smallest school districts for 2000. Additionally, parameterization B which explicitly uses county population size has lower median CVs than parameterization A across both years and both types of shares. These results are consistent with the evaluations done in Maples and Bell (2007, Section 4.2). It is not clear which parameterization, A or B, is a better estimator of the CVs. The smaller median CVs in parameterization B may understate the variability in the estimator. However, comparisons between estimators using the same parameterization are valid. The overall reduction in median CV by using the Minimum Change shares versus the previous census shares is around 20% and the reduction increases as the population size of the school district increases. The small negative reduction (an increase) for the smallest school districts could be due to the noisy nature of the data.

One major question is how much improvement in the precision of our estimates might we expect to see if we could lower the non-geocoding rate to under 10% for all counties. We address this by cross classifying the whole school districts by nongeocoding rate and population size. For population size we collapse the categories used in Table 9 to: <1000, 1000-5000, 5000+. To create a nongeocoding rate for the whole school district, we take a weighted average of the nongeocoding rates for the school district pieces, weighted by the school district piece population size. The categories for average nongeocoding rate for school districts are: 0-10%, 10-20%, 20-30%, 30-40%, 40+%. Sample sizes are given in Table 10. Tables 11 and 12 give the CVs for 2000 and 1990 under parameterization A and Tables 13 and 14 give the CVs for parameterization B. Tables 15 and 16 give the ratio of Minimum Change CV to the previous census shares CV. Note that for districts with high non-geocoding rates, the ratios are close to 100% in Tables 15 and 16 which are reasonable because Minimum Change method is typically showing little or no difference from the previous census shares for these districts. To determine the potential gain in precision by lowering the nongeocoding rates we average the percentage decrease in CVs from 1990 and 2000 for each parameterization for the Minimum Change estimator compared to the previous census share. Under parameterization A, suppose we can lower the nongeocoding rates to under 10% for all counties. We would expect to see an additional decrease (relative to the CVs from the Minimum Change estimator) of 23% (see below for calculation) for the smallest districts (<1000), 25% for the medium sized districts (1000-5000) and 11% for the largest districts (5000+). Similarly, under parameterization B, we would expect to see an additional decrease of 12%, 23% and 12% for the small, medium and large school districts, respectively. The largest districts have smaller percentages of tax returns that are not geocoded and thus less room for improvement by decreasing the nongeocoding rate. Even with these improvements, CVs for school district estimates are high as there have been no surveys designed to make direct estimates for all school districts. The American Community Survey is designed to produce estimates for all school districts once five years of data have been collected (the first set of estimates will use the 2005-2009 survey data). Also, the availability of auxiliary data (such as IRS income tax data) applicable for school district pieces is limited.

The expected decreases in CVs are calculated from the results in Tables 15 and 16. The decreases for the small school districts under parameterization A are shown.

1. Decrease in 2000: 1 -"0-10%" / "all rates" = 1-.722/1.008 = .28
2. Decrease in 1990: 1 -"0-10%" / "all rates" = 1 - .722/.889 = .18
3. Average the decreases from 2000 and 1990 is (.28+.18)/2 = 23%

5 Limitations

The methodology described in this report contains some strong assumptions and important limitations that will be explicitly listed here.

1. To evaluate estimators and variances, the best dataset to make direct estimates comes from the long-form survey of the decennial census. For school district pieces, these estimates have large relative errors (CVs) making it difficult to distinguish sampling error from estimation error.

2. In the Minimum Change method, sampling error variance in the previous census which anchors the Minimum Change estimates is not taken into account. This adds an additional source of error whose magnitude may vary across school districts. A similar argument can also be made for the previous census shares, as we do not take the previous census sampling error variance into account in the evaluation.

3. The 10-year time lag in the anchor dataset used in the Minimum Change and previous census share methods are likely to overstate the error when the anchor dataset is more current.

4. Results assume that the functional forms for $Var(y_{ij})$ and stratification on county size and geocoding rate for σ_k^2 gives reasonable approximation to the variance structure of the within-county shares.

5. We assume that the σ_k^2 will remain constant over time (evaluations with 1990 and 2000 censuses show that this is rather suspect) and that the 1990 and 2000 censuses are both "typical," in order to justify taking the average of the $\hat{\sigma}_k^2$'s for use in intercensal years.

6. In calculating the gains made by potential improvements in the geocoding rate of the IRS tax returns, we assume the geocoding improvements do not add additional bias due to erroneous geocoding, i.e. placing the tax return in the wrong school district piece.

References

Maples and Bell (2007), "Small Area Estimation of School District Child Population and Poverty: Studying Use of IRS Income Tax Data," *Statistical Research Division Research Report Series (Statistics #2007-11)*, U.S Census Bureau.

Table 1: Number of school district pieces by size and nongeocoding rate from the 2000 census and 1999 IRS income tax data

NG rate	<2500	2500-10k	10k-100k	100k+	all sizes
0%	292	428	193	21	934
0-10%	65	169	2226	1996	4456
10-20%	353	1878	2430	211	4872
20-30%	626	1612	1056	0	3294
30-40%	680	1136	519	16	2351
40+%	2081	1778	410	0	4269
all rates	4097	7001	6834	2244	20176

Table 2: Number of school district pieces by size and nongeocoding rate from the 1990 census and 1989 IRS income tax data

NG rate	<2500	2500-10k	10k-100k	100k+	all sizes
0%	312	432	171	19	934
0-10%	0	35	1291	1181	2507
10-20%	0	423	1627	462	2512
20-30%	34	590	1156	109	1889
30-40%	117	724	1003	0	1844
40+%	3756	5064	1654	16	10490
all rates	4219	7268	6902	1787	20176

Table 3: Cell groups that compose the 12 post-strata for estimation of σ_k^2

<table>
<tr><th>NG rate</th><th><2500</th><th>2500-10k</th><th>10k-100k</th><th>100k+</th></tr>
<tr><td>0%</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>0-10%</td><td rowspan="4">11</td><td rowspan="2">7</td><td>3</td><td>1</td></tr>
<tr><td>10-20%</td><td>4</td><td rowspan="4">2</td></tr>
<tr><td>20-30%</td><td>8</td><td>5</td></tr>
<tr><td>30-40%</td><td>9</td><td rowspan="2">6</td></tr>
<tr><td>40+%</td><td>12</td><td>10</td></tr>
</table>

Table 4: Estimates of σ^2_{Ak} under parameterization A using Minimum Change shares

Year	NG rate	<2500	2500-10k	10k-100k	100k+
2000	0-10%	.048	.021	.010	.003
	10-20%			.011	.002
	20-30%		.025	.008	
	30-40%		.020	.021	
	40+%	.061	.019		
1990	0-10%	.029	.013	.007	.009
	10-20%			.008	.003
	20-30%		.024	.011	
	30-40%		.019	.012	
	40+%	.062	.023		
wt avg	0-10%	.047	.019	.007	.005
	10-20%			.009	.003
	20-30%		.025	.011	
	30-40%		.020	.011	
	40+%	.062	.022		

Table 5: Estimates of σ^2_{Bk} under parameterization B using Minimum Change shares

Year	NG rate	<2500	2500-10k	10k-100k	100k+
2000	0-10%	7.09	10.34	15.91	50.35
	10-20%			18.62	46.27
	20-30%		12.06	21.99	
	30-40%		12.35	17.84	
	40+%	7.13	13.91		
1990	0-10%	7.57	10.68	17.91	167.25
	10-20%			19.07	38.96
	20-30%		17.72	22.72	
	30-40%		15.35	25.4	
	40+%	10.45	16.00		
wt avg	0-10%	7.13	10.40	16.64	93.76
	10-20%			18.78	40.99
	20-30%		13.58	22.37	
	30-40%		13.52	23.43	
	40+%	9.25	15.45		

Table 6: Estimates of σ^2_{Ak} under parameterization A using previous census shares

Year	NG rate	<2500	2500-10k	10k-100k	100k+
2000	0-10%	.058	.032	.023	.002
	10-20%			.018	.006
	20-30%		.026	.020	
	30-40%		.024	.010	
	40+%	.069	.022		
1990	0-10%	.029	.027	.022	.023
	10-20%			.022	.007
	20-30%		.033	.022	
	30-40%		.022	.020	
	40+%	.060	.027		
wt avg	0-10%	.055	.031	.023	.021
	10-20%			.019	.007
	20-30%		.028	.021	
	30-40%		.023	.018	
	40+%	.063	.026		

Table 7: Estimates of σ^2_{Bk} under parameterization B using previous census shares

Year	NG rate	<2500	2500-10k	10k-100k	100k+
2000	0-10%	8.56	15.85	46.95	269.10
	10-20%			32.18	141.69
	20-30%		12.70	39.70	
	30-40%		14.83	21.32	
	40+%	9.07	16.12		
1990	0-10%	7.35	22.39	57.89	443.73
	10-20%			52.56	94.38
	20-30%		24.13	47.21	
	30-40%		17.71	42.01	
	40+%	10.11	18.59		
wt avg	0-10%	8.46	17.03	50.96	333.96
	10-20%			40.39	107.52
	20-30%		15.77	43.63	
	30-40%		15.95	36.63	
	40+%	9.73	17.94		

Table 8: Ratio of σ_k^2 estimates (Minimum Change vs previous census shares) using weighted average of 2000 and 1990

Parameterization	NG rate	<2500	2500-10k	10k-100k	100k+
A	0-10%	84.8%	62.5%	32.2%	26.2%
	10-20%			47.7%	38.2%
	20-30%		88.2%	51.4%	
	30-40%		84.6%	63.8%	
	40+%	98.4%	86.4%		
B	0-10%	84.3%	61.1%	32.7%	28.1%
	10-20%			46.5%	38.1%
	20-30%		86.1%	51.3%	
	30-40%		84.8%	64.0%	
	40+%	95.1%	86.1%		

Note: values less than 100% indicate that Minimum Change shares had less prediction error compared to using previous census shares.

Table 9: Median CVs for whole school district estimates

		District Population Size					
year	Estimator	<500	500-1000	1000-2000	2000-5000	5000+	all districts
2000	CV Census long-form	.321	.237	.208	.164	.091	.216
	CV MC share (A)	.765	.438	.348	.294	.212	.437
	CV MC share (B)	.684	.404	.312	.245	.150	.382
	CV Cen share (A)	.698	.502	.436	.427	.352	.521
	CV Cen share (B)	.630	.473	.418	.361	.255	.464
1990	CV Census long-form	.420	.294	.217	.179	.104	.235
	CV MC share (A)	.738	.421	.335	.294	.209	.424
	CV MC share (B)	.625	.362	.292	.247	.161	.360
	CV Cen share (A)	.771	.502	.443	.436	.347	.548
	CV Cen share (B)	.654	.448	.402	.375	.263	.465
	number districts	4418	2356	2636	2936	1988	14334
	avg reduction in CV from Cen(A) to MC(A)	-2.6%	14.4%	22.2%	31.8%	39.8%	19.3%
	avg reduction in CV from Cen(B) to MC(B)	-2.1%	16.9%	26.4%	33.2%	40.0%	20.1%

Table 10: Number of whole school districts classified by size and average nongeocoding rate

year	nongeo rate	<1000	1000-5000	5000+
2000	0-10%	625	1620	1107
	10-20%	1148	1402	446
	20-30%	1070	852	209
	30-40%	1037	606	107
	40+%	2894	1092	119
1990	0-10%	295	956	692
	10-20%	486	918	476
	20-30%	483	568	215
	30-40%	590	568	151
	40+%	4920	2562	454

Table 11: Median CVs for 2000 estimates of number of children in poverty for whole school districts - Parameterization A

Estimator	nongeo rate	<1000	1000-5000	5000+
MC share (A)	0-10%	1.131	.564	.309
	10-20%	.711	.303	.133
	20-30%	.621	.273	.124
	30-40%	.603	.232	.118
	40+%	.536	.220	.121
	all rates	.620	.326	.212
Cen share (A)	0-10%	1.565	1.081	.597
	10-20%	.794	.431	.189
	20-30%	.589	.334	.168
	30-40%	.583	.279	.157
	40+%	.532	.247	.147
	all rates	.615	.433	.352

Table 12: Median CVs for 1990 estimates of number of children in poverty for whole school districts - Parameterization A

Estimator	nongeo rate	<1000	1000-5000	5000+
MC share (A)	0-10%	1.325	.813	.373
	10-20%	1.012	.441	.218
	20-30%	.827	.340	.154
	30-40%	.735	.314	.132
	40+%	.518	.223	.110
	all rates	.590	.318	.209
Cen share (A)	0-10%	1.835	1.402	.674
	10-20%	1.624	.756	.372
	20-30%	1.063	.484	.225
	30-40%	.963	.441	.193
	40+%	.574	.271	.144
	all rates	.663	.441	.347

Table 13: Median CVs for 2000 estimates of number of children in poverty for whole school districts - Parameterization B

Estimator	nongeo rate	<1000	1000-5000	5000+
MC share (B)	0-10%	1.006	.469	.216
	10-20%	.644	.268	.104
	20-30%	.567	.236	.097
	30-40%	.523	.204	.085
	40+%	.472	.189	.086
	all rates	.551	.279	.150
Cen share (B)	0-10%	1.175	.860	.409
	10-20%	.744	.393	.150
	20-30%	.586	.304	.137
	30-40%	.530	.253	.117
	40+%	.476	.214	.107
	all rates	.565	.392	.255

Table 14: Median CVs for 1990 estimates of number of children in poverty for whole school districts - Parameterization B

Estimator	nongeo rate	<1000	1000-5000	5000+
MC share (B)	0-10%	1.124	.642	.262
	10-20%	.944	.398	.180
	20-30%	.709	.285	.117
	30-40%	.586	.251	.102
	40+%	.448	.195	.092
	all rates	.506	.270	.161
Cen share (B)	0-10%	1.468	1.200	.498
	10-20%	1.303	.613	.311
	20-30%	1.047	.430	.170
	30-40%	.778	.356	.141
	40+%	.494	.235	.126
	all rates	.568	.388	.263

Table 15: Ratio of CVs - Minimum Change (A) over previous census share (A) for number of children in poverty for whole school districts by size and nongeocoding rate

year	nongeo rate	<1000	1000-5000	5000+
2000	0-10%	72.2%	52.1%	51.7%
	10-20%	89.5%	70.3%	70.3%
	20-30%	105.4%	81.7%	73.8%
	30-40%	103.4%	83.1%	75.1%
	40+%	100.7%	89.1%	82.3%
	all rates	100.8%	75.3%	60.2%
1990	0-10%	72.2%	57.9%	55.3%
	10-20%	62.3%	58.3%	58.6%
	20-30%	77.8%	70.2%	68.4%
	30-40%	76.3%	71.2%	68.3%
	40+%	90.2%	82.2%	76.3%
	all rates	88.9%	72.1%	60.2%

Table 16: Ratio of CVs - Minimum Change (B) over previous census share (B) for number of children in poverty for whole school districts by size and nongeocoding rate

year	nongeo rate	<1000	1000-5000	5000+
2000	0-10%	85.6%	54.5%	52.8%
	10-20%	86.5%	68.1%	69.3%
	20-30%	96.7%	77.6%	70.8%
	30-40%	98.6%	80.6%	72.6%
	40+%	99.1%	88.3%	80.3%
	all rates	97.5%	71.1%	58.8%
1990	0-10%	76.5%	53.5%	52.6%
	10-20%	72.4%	64.9%	57.8%
	20-30%	67.7%	66.2%	68.8%
	30-40%	75.3%	70.5%	72.3%
	40+%	90.6%	82.9%	73.0%
	all rates	89.0%	69.5%	61.2%