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DEVELOPMENT AND EVALUATION OF ALTERNATIVE STATE ESTIMATES OF POVERTY, FOOD STAMP PROGRAM ELIGIBILITY, AND FOOD STAMP PROGRAM PARTICIPATION

FINAL REPORT

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EXECUTIVE SUMMARY

Recent evidence suggesting widening regional differences in demographic and economic conditions has raised concerns among policymakers that some areas of the United States are profiting little from economic expansions and suffering disproportionately from economic contractions. Further concerns have been raised about the impact of social welfare programs, such as the Food Stamp Program (FSP), in depressed areas. These concerns have elicited questions about whether the benefits of our social welfare system are distributed equitably across the nation according to need and have intensified the demand for subnational estimates of indicators of well-being and indicators of program effectiveness.

The Food and Nutrition Service (FNS) seeks estimates of State poverty counts, State FSP eligibility counts, and State FSP participation rates. The FSP participation rate is a key measure of program effectiveness. The purpose of this study is to assess the suitability of alternative estimation methods, to derive the estimates requested by FNS, and to evaluate the estimates obtained.

We ***consider five small-area estimation methods*** that can be used to obtain estimates of State poverty counts, State FSP eligibility counts, and State FSP participation rates:

1. The direct sample estimation method
2. The regression method
3. The ratio-correlation technique
4. Shrinkage methods
5. Structure preserving estimation (SPREE)

After weighing the relative advantages and disadvantages of all five methods, we recommend three methods-the direct sample estimation method, the regression method, and shrinkage methods-for empirical application and testing. We ***recommend against the empirical application and testing of the ratio-correlation technique*** and *SPREE* for two principal reasons. First, both methods are computationally burdensome, requiring that we process census microdata to obtain FSP eligibility estimates. Second, both methods assume that the relationships between poverty or FSP eligibility and various socioeconomic and demographic indicators are stable, that a model estimated using census data pertains for each year until data from the next census are available. For this study, we would have to use 1980 census data However, we have no reason to believe that the relevant multivariate relationships have remained stable over time, in general, and over the 1980s, in particular. Witb no evidence suggesting that either the ratio-correlation technique or SPREE strongly dominates the regression or shrinkage methods in terms of lower sampling variability, we believe that it is prudent to avoid the potential biases from assuming temporal stability.

Each of the three estimation methods recommended for empirical application and testing requires sample data. The leading candidate data sources are the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP). *We **recommend against using SIPP as*** a source of sample data for this study because (1) SIPP, which is not designed for State estimation, provides small State sample sizes and, therefore, supports much less precise sample estimates than the CPS and (2) SIPP uniquely identifies only 42 States, including the District of Columbia.

Using CPS data and administrative records data such as data from vital statistics records, we obtain direct sample estimates, regression estimates, and shrinkage estimates of State poverty *counts, State FSP eligibility counts, and State FSP participation rates for 1986, 1987,* and 1988. We also derive estimates of State poverty rates and State FSP eligibility rates. Our shrinkage estimator is a hierarchical Empirical Bayes estimator that optimally combines direct sample estimates and regression estimates.

In our empirical evaluation of the direct sample, regression, and shrinkage methods, we fmd that the *three methods generally agree on aggregate characteristics pertaining to the distribution of* State *estimates.* For the distribution of State FSP participation rates, for instance, such aggregate characteristics include the median State participation rate, the national participation rate implied by the State estimates, the standard deviation or interquartile range of the State participation rates, and the distribution of the State participation rates across broadly defined categories. The direct sample, regression, and shrinkage methods also generally agree on which areas of the country tend to have higher participation rates and which areas tend to have lower participation rates.

Despite this general agreement among the direct sample, regression, and shrinkage methods on aggregate features of the distribution of State estimates, we find that for some States, the three alternative estimates for a given year differ substantially. For example, differences of four percentage points between direct sample and regression estimates of FSP participation rates are common. Some of the observed differences in point estimates, however, can be attributed largely to sampling variability. When we compare interval estimates, that is, confidence intervals, we find that *the regression and shrinkage methods mainly reduce our uncertainty, providing narrower confidence intervals than the direct sample estimation method.* For some States, the confidence intervals from the regression method and, to a much lesser degree, the shrinkage method include values that we would consider unlikely based even on the relatively wide confidence intervals from the direct sample estimation method. But for most States, the regression and shrinkage methods imply confidence intervals that he entirely inside the confidence intervals implied by the direct sample estimation method.

Although each of the three estimation methods has relative strengths and weaknesses, we *recommend our shrinkage estimates over our direct sample estimates and regression estimates.* We recommend shrinkage estimates over direct sample estimates primarily because our shrinkage estimates are substantially more reliable for many States. Overall, we find that the shrinkage estimator is statistically more efficient than the direct sample estimator. We recommend shrinkage estimates over regression estimates for three reasons. First, for the nation as a whole and for States for which we obtain precise direct sample estimates, we find substantially closer agreement between direct sample and shrinkage estimates than between direct sample and regression estimates. Differences between shrinkage and direct sample point estimates are much smaller than differences between regression and direct sample point estimates. Also, the overlap between confidence intervals implied by shrinkage and direct sample estimates is greater than the overlap between confidence intervals implied by regression and direct sample estimates. Second, although the standard errors of regression estimates are much smaller than the standard errors of shrinkage estimates for some States, we believe that our estimated standard errors exaggerate the overall precision of the regression estimates. We find that the covariances between regression estimates for different States are relatively large. Thus, the risk of obtaining many large estimation errors is higher with the regression method than with the direct sample and shrinkage methods. The covariances between regression estimates for different States are sufficiently large that despite relatively small standard errors of regression estimates for individual States, the regression estimator cannot be judged statistically more efficient than the shrinkage estimator or even the direct sample estimator. Third, we find that the shrinkage estimator is less sensitive to model specification than the regression estimator. We find that similar regression models can yield moderately to substantially different estimates for some States. By combining the regression estimates with direct sample estimates, the shrinkage estimator dampens differences between estimates from competing models.

I. INTRODUCTION

Recent evidence suggesting widening regional differences in demographic and economic conditions has raised concerns among policymakers that some areas of the United States are profiting little from economic expansions and suffering disproportionately from economic contractions. Further concerns have been raised about the impact of social welfare programs, such as the Food Stamp Program (FSP), in depressed areas. These concerns have elicited questions about whether the benefits of our social welfare system are distributed equitably across the nation according to need and have intensified the demand for subnational estimates of indicators of well-being and indicators of program effectiveness.

The Food and Nutrition Service (FNS) seeks estimates of State poverty counts, State FSP eligiiity counts, and State FSP participation rates. The FSP participation rate is a key measure of program effectiveness.[1] The purpose of this study is to assess the suitability of alternative estimation methods, to derive the estimates requested by FNS, and to evaluate the estimates obtained.

National poverty estimates are published annually by the Census Bureau. Although there is ongoing debate about how to measure the incidence of poverty, national estimates of poverty are statistically reliable, even for major population subgroups. Nevertheless, due largely to data limitations, reliable estimates of State poverty rates cannot be obtained as easily. The Current Population Survey (CPS), from which the Census Bureau's national estimates are derived, has a State-based design and provides representative samples in each State. However, its sample sizes for many States are small and do not support precise sample estimates.[2]

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[1]The FSP participation rate is obtained by dividing the number individuals or households receiving food stamps by the number of FSP eligible individuals or households. The FSP participation rate can also be measured by dividing the dollar amount of food stamp benefits that are distributed by the dollar amount of food stamp benefits for which households are eligible.

[2]After the first draft of this report was submitted, the Census Bureau published for the first time ever CPS poverty estimates for States. The estimates are accompanied by the warning that they (continued...)

Ross and Danziger (1987) estimated State poverty rates for 1979 and 1985 using CPS data However, their estimates for many States were subject to high sampling variability-standard errors exceeded 1.5 percent for most States and were at least 20 percent for many States. The margin of error in Ross and Danziger's (1987) sample estimate of 18 percent for Iowa's 1985 poverty rate, for example, was over four percentage points, meaning that they could conclude only that Iowa's poverty rate was probably between 14 percent and 22 percent? This margin of error would be unacceptable for many purposes. Plotnick (1989) and Haveman, Danziger, and Plotnick (1991) derived State poverty rate estimates with smaller standard errors by combining CPS samples for three consecutive years and dropping overlapping observations from the first and third years.[4] This approach produced estimated poverty rates that, although statistically more reliable, were difficult to interpret, The estimated rates measured the average incidence of poverty across three years, rather than the incidence of poverty in one year. When the objective is to make geographic comparisons, averaging poverty rates in this way is inappropriate because the pace of economic change likely varies among States. Poverty rates surely rise and fall more quickly in some States and more slowly in other States.

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[2](...continued)
"should be used with caution since [they have] relatively large standard errors" (U.S. Department of Commerce, 1991). We discuss these estimates in greater detail in Chapter V.

[3]This range is the 95 percent confidence interval for Iowa's 1985 poverty rate. The boundaries were obtained by taking roughly twice the standard error above and below the estimated poverty rate. Prior to selection of a particular sample, a confidence interval constructed in this way contains Iowa's true 1985 poverty rate with probability 95 percent. The estimated standard error obtained by Ross and Danziger (1987) was 213 percent.

[4]This approach doubled sample sizes and reduced standard errors by nearly 30 percent. To reduce the sampling error associated with estimates of change in monthly unemployment rates (and to reduce data collection costs), the CPS uses a "rotation group" design in which one-half of the selected households in consecutive annual samples are the same. (For monthly unemployment estimates, threequarters of the selected households in consecutive monthly samples are the same.) Thus, it is necessary to pool not two but three March CPS samples to double the effective sample size. Half of the households in the middle year's sample are in the first year's sample, and the other half are in the third year's sample. The usual procedure for constructing a pooled three-year estimate--but an arbitrary choice from among several procedures-is to weight the middle year twice as heavily as each of the other two years by counting all of the sample observations in the middle year and only the nonoverlapping observations in the first and third years.

The previously noted uneven weighting of the three years detracts further from the interpretability of the pooled estimates? To address the shortcomings in sample estimates, Dunton and Leon (1988) used regression methods to estimate the extent of poverty in New York State counties for each year from 1980 to 1986. However, their approach required the implausible assumption that the relationships between poverty and various economic indicators remain stable over time.

Precise estimates of the FSP participation rate are available at the national level. For example, Trippe, Doyle, and Asher (1991) estimated national FSP participation rates biannually from 1976 to 1988 using CPS data. However, as with poverty, precise subnational estimates of FSP eligibility or participation cannot be easily obtained. Czajka (1981) used the structure preserving estimation (SPREE) method and data from various sources including the 1970 census and the 1979 CPS to derive FSP participation rates for food stamp counties as of October 1979. The Physician Task Force on Hunger in America (1986) used published estimates for counties from the 1980 census and published estimates for regions from the 1985 March CPS and developed a crude adjustment procedure to identify the joint incidence of high poverty and low FSP participation at the county level. The Task Force sought only to determine whether a county had a poverty rate above 20 percent and an FSP participation rate below 33 percent and made no attempt to measure sampling variability in estimates obtained.

With respect to the central goal of this study, a primary shortcoming of these previous studies of poverty and FSP participation is that they do not evaluate alternative estimation methods and estimates. Several of the studies, moreover, use methods that are not suitable for deriving estimates for States or smaller areas.

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[5]Pooling also limits the ability to compare estimates over time. Pooled estimates for consecutive years will incorporate two overlapping years-the second and third years pooled to obtain the first estimate are the first and second years pooled to obtain the second estimate--implying that half of the observations on which each pooled estimate is based will consist of the same households measured at the same point in time. Because of this 50 percent overlap for which no changes can be observed, a comparison of the two pooled estimates will generally understate the year to year change.

This study examines five leading estimation methods. After weighing the conceptual and practical strengths and weaknesses of the five methods, we recommend three methods for empirical application and testing. We derive State poverty, FSP eligibility, and FSP participation estimates using each of the three methods and evaluate the estimates obtained.

The remainder of this report consists of five chapters and three appendixes. Chapter II discusses so-called "small-area" estimation methods and the data required by those methods. The relative strengths and weaknesses of alternative estimation methods and data sources are assessed. Chapter III resolves several preliminary empirical issues, such as how to measure the FSP eligibility status of households and individuals using CPS data. Chapter IV describes our estimation procedures for obtaining State estimates of poverty, FSP eligibility, and FSP participation and for measuring the precision of the estimates obtained Chapter V presents our empirical results and assesses State estimates obtained using alternative estimation methods. Chapter VI summarizes our results and offers recommendations based on those results. Appendix A describes our procedure for simulating the. FSP eligibility status of households and individuals in the CPS. Appendix B defines the "symptomatic indicators" used in our regression models of poverty and FSP eligibility. Appendix C presents the regression models identified as the best models by our model fitting procedure.

II. ALTERNATIVE ESTIMATION METHODS

For obtaining State poverty counts and State FSP eligiiity counts, five leading methods of small-area estimation are most appropriate for consideration.. The five estimation methods are:

1. Direct sample estimation
2. The regression method
3. The ratio correlation technique
4. Shrinkage methods
5. Structure preserving estimation (SPREE)

The first five sections of this chapter discuss in detail each of these estimation methods and their strengths and weaknesses. The final section of this chapter weighs the relative advantages and disadvantages of the five methods and offers recommendations for empirical application and testing. We recommend against empirical application and testing of the ratio-correlation technique and SPREE. Although our discussion of each method is often framed in terms of estimating poverty counts, it also applies to eligibility counts. Instances in which the estimation of eligibility counts raises additional or different issues are noted. Chapter III describes our procedures for determining poverty status and FSP eligibility status using sample (CPS) data. Chapter IV describes our estimation procedures for the methods that we recommend for empirical application.

A. DIRECT SAMPLE ESTIMATION

Direct sample estimation involves simply calculating the poverty count for each State using sample data obtained from, for example, the Current Population Survey (CPS) or the Survey of Income and Program Participation (SIPP). An advantage of direct sample estimation is its simplicity.

Another advantage is that it yields estimates that are unbiased, that is, correct on average.[1] The principal disadvantage of direct sample estimates is that, although they are unbiased they are subject to substantial sampling variability for some, if not many, States.

The only data required for direct sample estimation are sample survey data. The two leading sources of sample survey data for this study are the CPS and SIPP.

The CPS offers several important advantages. One advantage of the CPS is that it has a State-based design, providing representative samples for each State and the District of Columbia[2] A second advantage is that the kind of data required for our study are available every year (from the March supplement) and are available for use with the documentation needed for State estimation relatively soon (typically within nine months) after the data are collected. A third advantage of the CPS is that it is the primary database for the MATH® microsimulation model, which is used to derive FSP eligibility estimates with well-known strengths and weaknesses. Although this study uses a somewhat cruder method for simulating FSP eligiiility from CPS data, the method's results compare favorably with the results obtained from the more refined MATH model simulations (Trippe, Doyle, and Asher, 1991).[3]

The main disadvantage of the CPS is that it provides limited data on crucial determinants of program eligibility. For example, the CPS identifies a household, a group of individuals sharing living quarters, but not a food stamp unit, a group of individuals sharing food purchases and preparation![4]

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[1]Strictly, not all direct sample estimates, including some of the estimates of greatest interest in this report, are unbiased. Because its denominator is a sample estimate, like its numerator, the direct sample estimate of an adjusted FSP participation rate is a so-called "ratio mean" (Kish, 1965). Ratio means are necessarily biased. The denominators of our direct sample estimates of poverty and FSP eligibility rates are also based on sample estimates. (We subtract a sample estimate of the number of unrelated individuals under age 15 from a nonsample estimate of the State population to obtain the denominator for a rate.) Thus, direct sample estimates of rates are ratio means

[2]Throughout this report, the District of Columbia is counted as a "State"

[3]Our simulation procedure is described in Chapter III and Appendix A

[4]There are exceptions to this definition of a food stamp unit. One exception pertains to households with elderly individuals who are unable to prepare their own meals.

Also, the CPS does not gather sufficient data on asset balances and deductible expenses to determine FSP eligibility and obtains only annual income information, whereas FSP eligibility is assessed on a monthly basis.

The primary advantage of SIPP is that it supports much more accurate FSP eligibility determinations than the CPS. Food stamp units can be identified with SIPP data (although only for FSP participants). SIPP obtains monthly income data and periodic data on asset balances and deductible expenses. SIPP also captures changes in family composition.[5]

An important disadvantage of SIPP is that, relative to the CPS, SIPP sample sizes are small and support less precise estimates. The Census Bureau has wamed that SIPP is "not designed to produce State estimates" and that SIPP 'estimates for individual States are subject to very high variance and are not recommended (U.S. Department of Commerce, 1992)."[6] Another critical disadvantage of SIPP is that State of residence cannot be uniquely identified, preventing the derivation of estimates for all 51 States. Sample estimates cannot be obtained for Maine and Vermont, which are grouped together as one State;" for Iowa, North Dakota, and South Dakota, which are grouped together; and for Alaska, Idaho, Montana, and Wyoming, which are grouped together. One other disadvantage of SIPP data is the relative lack of timeliness. SIPP data are often unavailable until 12 to 18 months after data collection.

We are assuming throughout this report that State estimates are required for a year for which census data are not available. Otherwise, we recommend deriving small-area estimates from census data if the census obtains reliable information on the variables required and if sufficient resources are available to process census data Small-area estimates based even on subsamples of census

[5]As we note in Chapter V, national participation rates estimated using CPS data are lower than national participation rates estimated using SIPP data

[6]To assist data users in calculating standard errors that reflect the complex sample designs of the CPS and SIPP, the Census Bureau publishes values for the parameters of generalized variance functions. The Census Bureau publishes State-specific parameter values for the CPS. However, the Census Bureau does not publish parameter values for estimating standard errors for State estimates derived from SIPP data.

records will be more precise than estimates calculated from the largest sample surveys. The disadvantages of using census data are discussed in Section C.

B. THE REGRESSION METHOD

The objective of the regression method is to "smooth" direct sample estimates, that is, to reduce their sampling variability. Although direct sample estimates may not always be sufficiently reliable to satisfy users' needs, the direct sample estimates can be used to produce potentially better estimates. Originally developed by Ericksen (1974), the regression method of small-area estimation combines sample data with symptomatic information, using multivariate regression to reduce sampling error and enhance accuracy. The basic model is:

$$\text{(II.1)} \qquad Y = XB + u,$$

where Y is a (51 x 1) vector of State-level sample estimates on a criterion variable, such as poverty incidence, and X is a (51 x p) matrix containing data for each State on a set of p − 1 predictor variables or symptomatic indicators.[7,8] B is a (p x 1) vector of parameters to be estimated u is an error term--a (51 x 1) vector-reflecting both the inability of the symptomatic indicators to explain interstate variation in the criterion variable and the fact that sample measurements of the criterion variable are subject to sampling error.' The regression estimator is:

'One of the p columns in X is for a constant term (intercept) taking a value of one for all 51 States.

[8]We do not give the regression model a causal interpretation. That is, we do not assert that the variables in X cause Y. Instead, we claim only that the variables in X are associated with Y. Therefore, the variables in X are called "symptomatic indicators" rather than "explanatory variables." Also, because we are deriving regression estimates only for the areas for which we already have sample estimates and, thus, are not "predicting" values in the usual sense, we favor "symptomatic indicators" over "predictor variables."

[9]Equation (1) is obtained as follows. Suppose that the vector of true values on the criterion variable is Y_T and that Y_T = XB + v. v captures the inability of the variables in X to "explain interstate variation in Y_T. Suppose also that the direct sample estimates are related to the true values according to Y = Y_T + w. w captures sampling variability in the direct sample estimates. Combining the expressions for Y and Y_T gives Y = XB + v + w = XB + u, where u = v + w.

$$(II.2) \quad \hat{Y} = X\hat{B},$$

where $\hat{B}$ is the least squares regression estimate of B. Regression estimates of the criterion variable, the elements of $\hat{Y}$, are biased.[10] However, regression estimates may improve upon sample estimates according to an overall accuracy criterion, such as mean square error (MSE), which accounts for error from both bias and sampling variability.[11]

The regression method requires data on Y, the criterion variable, and data on X, the set of symptomatic indicators. Data on Y are obtained from a sample survey. The elements of Y are direct sample estimates. The strengths and weaknesses of the two primary sample surveys were discussed in the previous section.

Data on the symptomatic indicators can come from various sources, including a census and administrative records.[12,13] Administrative records include birth certificates, immigration forms, tax returns, Supplemental Security Income (SSI) case&s, and police crime reports. The principal limitation of census data for regression method estimation is the lack of timeliness. The regression

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[10] The bias in an estimator is the difference between the expected value of the estimator and the true value of the variable being estimated, Because the expected value of v is zero, the expected value of Y_T is $E(Y_T) = XB$. Because the expected values of v and w and, thus, u are zero, the expected value of Y is $E(Y) = XB$. If $\hat{B}$ is obtained by ordinary least squares, $\hat{B} = (X'X)^{-1}X'Y$ and $\hat{Y} = X\hat{B} = X(X'X)^{-1}X'Y$. The expected value of $\hat{Y}$ is $E(\hat{Y}) = X(X'X)^{-1}X'E(Y) = X(X'X)^{-1}X'XB = XB$. Therefore, $\hat{Y}$ is unbiased for $E(Y_T)$. $\hat{Y}$ is not, however, unbiased for Y_T. The bias is $E(\hat{Y}) - Y_T = XB - XB - v = -v$. Values of the elements of v are unknown.

[11] In applications in which the objective is to estimate a single value, the MSE of an estimator is the bias squared plus the variance. The variance is the standard error squared. For this study, in which 51 estimates are required, the MSE is represented by a matrix We describe the form of the MSE matrix in Chapter IV.

[12] Data on symptomatic indicators could be obtained from a sample survey. Although sample estimates of symptomatic indicators would be subject to sampling variability, the estimates could be treated as nonstochastic, as is typically done in regression analyses involving survey data outside the context of small-area estimation. (Except in extreme cases, least squares estimates lose their desirable properties in the presence of stochastic regressors) Nevertheless, for the purposes of small-area estimation, it seems desirable to consider only symptomatic indicators that are substantially more precise than the criterion variable.

[13] Estimates obtained by other methods, such as the ratio-correlation technique, have been included as symptomatic indicators (Ericksen, 1974).

method was proposed for small-area estimation to allow current sample data to be exploited. Unless it is believed that a symptomatic indicator has a lagged effect on the criterion variable, the symptomatic indicator should pertain to the same period as the criterion variable. Thus, in the absence of lagged effects, using "old" census data on symptomatic indicators means using "old" rather than current survey data. Other strengths and weaknesses of census data are discussed in the next section.

The principal limitation of administrative records data is that such data may provide relatively few symptomatic indicators. The reasons for this limitation are that a potential symptomatic indicator is not available for all States, data are not comparable across States, and State-level data are not available on a regular basis or are not available in a timely fashion.[14]

C. THE RATIO-CORRELATION TECHNIQUE

The ratio-correlation technique is similar to the regression method except that the ratio-correlation technique estimates the relationship between the criterion variable and the symptomatic indicators for the most recent year for which census data are available. Assuming that the estimated relationship remains stable over time, the ratio-correlation technique produces State-level estimates of the criterion variable using the estimated census-year regression equation and current-period values of the symptomatic indicators from, typically, administrative records data_ The ratio-correlation technique estimator is:

$$\text{(II.3)}\quad \hat{Y} = X\hat{B}_c$$

where $\hat{B}_c$ is the least squares regression estimate of B obtained using census data on the criterion variable and X is, as for the regression method, a matrix containing data for all States on a set of symptomatic indicators. For estimating $\hat{B}_c$ the data on the symptomatic indicators pertain to the

[14]Although sampling error may be absent from administrative records data, important sources of nonsampling error sometimes cannot be ruled out.

same time period as the census data on the criterion variable (the year before the census if the criterion variable is poverty incidence). For estimating $\hat{Y}$, the data on the symptomatic indicators should pertain to the year for which small-area estimates are desired, which could be several years after the census. The central assumption of the ratio-correlation technique is that B is stable over time.

The primary advantage of the ratio-correlation technique is that State poverty estimates based on the census are subject to substantially lower sampling error than are estimates derived from a survey like the CPS. The primary disadvantage of the ratio-correlation technique is that multivariate relationships are likely to change over time and, thus, that a model for, say, 1980 will not pertain today.

As noted, the ratio-correlation technique requires data on the symptomatic indicators for two time periods: the year to which the census data on the criterion variable pertain (and for which the regression equation is estimated) and the year for which State estimates are desired Data for both years would be obtained from the same sources-~ administrative records--discussed in the previous section. However, the ratio-correlation technique places a greater burden on administrative records systems than does the regression method. Data on a symptomatic indicator must be available for two specific years and must allow the symptomatic indicator to be defined the same way for the two years.

In addition to administrative records or similar data on symptomatic indicators, the ratio-correlation technique requires census data on the criterion variable. The principal advantage of census data is that they provide precise estimates, even for small geographic areas. For producing small-area population estimates, possibly broken down by age and sex, the decennial census is strongly preferred because, in principle, it provides complete counts that are not subject to sampling error. The census collects some information, however, on a sample basis using the "long form,' and it is important to understand that, for the criterion variables considered in this study, the census is a sample survey, albeit a very large sample survey providing a sample far larger than the sample available from any alternative data collection activity. Determining the poverty status of an individual, a household, or a family requires data on income, and income is a long-form item in the census. Census long forms are distributed to about **one in every five** to six housing units across the country as a whole. Given this sampling rate, the standard error for a poverty rate estimate of 14 percent would be on the order of 0.1 percent in the smallest State in 1980--Alaska, with a population of nearly 402,000.[15,16] Even if the CPS sample for each state were a simple random sample, the smallest standard error for a poverty rate estimate of 14 percent would be about 0.4 percent. Thus, the census supports much more precise sample estimates than a survey such as the CPS.

The principal disadvantage of census data is lack of timeliness along two dimensions. First, long-form census data are typically not available until about two to three years after the census is taken. Second, census data are available only every ten years. Long-form data from the 1990 census are not yet available for this study, and 1980 census data on income pertain to 1979.

A less serious disadvantage is that census data, like CPS data, permit only a crude determination of FSP eligibility. Nevertheless, it should be possible to simulate FSP eligibility from census data using a procedure similar to the procedure for simulating FSP eligibility from CPS data."

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[15]For purposes of approximation, it was assumed that the long-form census is a 19 percent random sample of persons. The standard error for a poverty rate estimated from a random sample of size n is $[p(1-p)/n]^{1/2}$, where p is the poverty rate. The standard error given in the text was calculated as the square root of $[0.14 \times (1 - 0.14)] \div (0.19 \times 402{,}000)$. Long forms are not distributed according to a simple random sample design.

[16]Using CPS data in Chapter V, we fmd that Alaska's 1988 poverty rate estimate of 113 percent has a standard error of 1.8 percent.

"Unlike the CPS, the census does not obtain data on separate amounts received from unemployment compensation, veteran's benefits, pensions, alimony, child support, and other regular sources of unearned income. Thus, the methods used for allocating annual income from these sources across months would have to be modified to accommodate census data. Therefore, simulations of FSP eligibility status based on census data would be somewhat cruder than simulations based on CPS data. Our procedure for simulating FSP eligibility from CPS data is described in Chapter III and Appendix A. Another problem for estimating both eligibility and poverty, underreporting of income, is probably more extensive in the census than in the CPS.

Simulating FSP eligibility, however, raises an important disadvantage of using census data--computational burden. Estimating State poverty counts using the ratio-correlation technique requires only census estimates of State poverty counts, which are readily available from Census Bureau publications. Estimating State FSP eligibility counts using the ratio-correlation technique requires census estimates of State FSP eligibility counts, which could be obtained only by processing a census microdata file and simulating each person's or household's FSP eligibility status before aggregating across observations within each State. Many microdata records would have to be processed, even if a sample of long-form returns were used.[18]

D. SHRINKAGE METHODS

Shrinkage methods calculate weighted averages of estimates obtained using other methods. For example, rather than discarding direct sample estimates in favor of regression estimates, an appealing strategy is to find a compromise, to use both sets of estimates to obtain better estimates. Shrinkage methods can be used to find a compromise and to exploit the unbiasedness of direct sample estimates and the low sampling variability of regression estimates. The class of shrinkage estimators contains several members, including James-Stein, Bayes, and Empirical Bayes estimators. The common feature of all shrinkage estimators is that, according to a criterion such as minimum MSE, shrinkage estimators optimally combine alternative estimates of the variable of interest by weighting according to relative reliability. A highly reliable poverty estimate is weighted more heavily and, thereby, influences more strongly the final wmbined poverty estimate than a less reliable poverty estimate, which receives a smaller weight and influences less strongly the combined poverty estimate. Thus, a shrinkage estimator would place a large weight on the sample estimate for a large State and a small

[18]Another approach (Czajka, 1981) would be to estimate relationships between numbers in poverty and numbers eligible for the FSP and to use the estimated relationships to derive "ratio-correlation estimates" of FSP eligibility counts from ratio-correlation estimates of poverty counts. In this study, such au approach would assume an answer where an answer is being sought. There would be built-in relationships between FSP eligibility and poverty that extend beyond the relationships attributable to FSP eligibility criteria

weight on the sample estimate for a small State. Shrinkage procedures were introduced as methods for small-area estimation by Fay and Herriott (1979), who formed a weighted average of sample and regression estimates of per capita income for small places (population less than 1,000) receiving funds under the General Revenue Sharing Program. Weights on the former reflected sampling error, while weights on the latter reflected lack of fit of the regression. The general form of a shrinkage estimator is:

$$\text{(II.4)} \qquad \hat{Y}_s = c\,\hat{Y}_1 + (1 - c)\,\hat{Y}_2,$$

where $\hat{Y}_s$ is the shrinkage estimator that combines the alternative estimators $\hat{Y}_1$ and $\hat{Y}_2$, c is the weight on $\hat{Y}_1$, $(1 - c)$ is the weight on $\hat{Y}_2$, and $0 \leq c \leq 1$. $\hat{Y}_1$ could be a vector of direct sample estimates, and $\hat{Y}_2$ could be a vector of regression estimates, as in Fay and Herriott (1979).

Shrinkage estimators are biased by design. Such bias is accepted in the pursuit of substantially lower sampling variability- Thus, the principal advantage of shrinkage estimators is that they optimally combine alternative estimates to minimize some overall measure of error that reflects, for example, both bias and sampling variability. Although a direct sample estimate may have the minimum sampling error among unbiased estimators, that minimum may be large relative to the sampling error of some slightly biased estimator. A shrinkage estimator may offer much lower sampling error at little cost in terms of bias.

The principal disadvantage is that a shrinkage estimator may not be robust to violations of certain underlying assumptions-for example, an assumption that a particular parameter takes a specified value. A small change in an assumed value may cause large changes in shrinkage estimates. Sensitivity analyses, which assess the effects of changes in assumptions, can often reveal such nonrobustness.

Different shrinkage estimators can require different data, depending on the estimators being combined. Fay and Herriott (1979) and Ericksen and Kadane (1987) used shrinkage methods that combined direct sample estimates and regression estimates. Therefore, the data requirements were the same as for the regression method. In gene& to obtain State poverty estimates, a shrinkage estimator would not use data other than sample survey, census, or administrative records data The strengths and weaknesses of each of these data sources have been discussed in the previous three sections.

E. STRUCTURE PRESERVING ESTIMATION (SPREE)

SPREE uses current sample data to update a table of estimates based on data from the last census. Developed by Purcell (1979), SPREE is a categorical data analysis approach to small-area estimation. The first step is to cross-tabulate a variable of interest, such as poverty, by variables thought to be associated with poverty.[19] The cross-tabulation is done for an earlier period when precise small-area estimates are available-from a census, for example. All variables must be expressed categorically. Poverty is measured in terms of poverty status, a dichotomous variable reflecting whether a person was in poverty or was not in poverty (if the individual is the unit of analysis). As a simple example, poverty status could be cross-classified by State of residence and age (elderly/nonelderly). Then, the number of persons in each cell of the resulting table, representing a unique combination-of one poverty status, one State, and one age category, would be calculated from census data The cells in this table describe an association structure among the three variables, that is, how poverty status and State of residence are related and how that relationship varies according to age, for instance.

Although a sample survey for the current period may not support reliable estimates of the values in each cell of the table, it can provide fairly precise values of marginal counts, such as State population totals by age and national estimates of poverty status by age. The second step of the SPREE method is to estimate from sample survey data the marginal counts for which direct sample

[19]These "associated variables" are analogous to the symptomatic indicators used in the regression method.

estimates of satisfactory precision can be obtained. Which margins satisfy such a condition is a matter of judgment_ The greater is the sampling error in marginal counts, the greater is the sampling error in SPREE estimates.

In the third step, SPREE uses a raking method of iterative proportional fitting to adjust cell values in the old table based on census data to match the new marginal frequencies derived from the sample survey. The survey estimates serve as control values for updating the cross-tabulation of poverty status by State by age. Bishop, Fienberg, and Holland (1975) describe iterative proportional fitting procedures,

An important advantage of the SPREE method is that it preserves that part of the original association structure not respecified by the new marginal totals; SPREE assumes that relationships are stable if there is no evidence of change from current sample data. Another critical advantage is that, in contrast to the regression method, SPREE requires sample data on characteristics of relatively low incidence only for larger geographic areas than those for which estimates are ultimately desired For this study, national--rather than State--sample estimates are needed for us to obtain State estimates using SPREE. The principal disadvantage of SPREE is that SPREE estimates are biased to the extent that current data do not reveal changes in the association structure estimated from earlier data. Another disadvantage is the computational burden of cross-tabulating census data.[20]

Census and sample survey data are required by the SPREE method. Census data are required for the original cross-tabulation of poverty status by associated variables, and sample survey data are required to update marginal totals. The strengths and weaknesses of these data sources have been discussed in the previous sections of this chapter. The only additional consideration is that the SPREE method imposes greater demands on census data than does the ratio-correlation technique, the other method that uses census data. The ratiocorrelation technique requires a census estimate of the incidence of poverty in each State. The SPREE method requires a census estimate of the

[20]It may be possible to use published cross-tabulations or, like Czajka (1981), to purchase cross-tabulated census data at a reasonable cost.

incidence of poverty in a subgroup, such as the elderly, in each State The latter estimate may be substantially less precise than the former.

F. RECOMMENDATIONS FOR EMPIRICAL APPLICATION OF ESTIMATION METHODS

Two of the five small-area estimation methods described in the previous sections--the ratio-correlation technique and SPREE--require census data. We recommend against the empirical application and testing of these two methods.

For our empirical application of the other three small-area estimation methods--the direct sample estimation method, the regression method, and shrinkage methods-each requiring sample data, we recommend the CPS as the source of the sample data. We cannot recommend SIPP as a source of sample data for this study because (1) SIPP, which is not designed for State estimation, provides small State sample sizes and (2) SIPP uniquely identifies only 42 States.[21]

We recommend against the empirical application and testing of the ratio-correlation technique and SPREE for two basic reasons. The first reason pertains to the assumption of temporal stability

[21] An alternative approach, which is beyond the scope of this study, is to use both CPS and SIPP data: SIPP data for the largest States and CPS data for the remaining States. For the large States, such an approach could substantially reduce the nonsampling error associated with the previously discus& limitations of CPS data on income, assets, and family composition with possibly only a modest increase in sampling error from the smaller SIPP sample sizes. Also, the regression and shrinkage estimators might "transfer" some of the reduction in nonsampling error to the smaller States. We are aware of no applications of this mixed approach, however, and cannot recommend it without further study. There are several potential problems with the approach. First, comparisons of States may be hampered by the different sources and relative magnitudes of nonsampling errors associated with CPS and SIPP estimates. Errors that are effectively eliminated by taking the difference between two States' estimates may no longer be eliminated when the estimates are obtained from different data. In some cases, SIPP and CPS data may be conceptually different, further limiting comparability. Second, because the SIPP estimates would be less precise (have higher sampling variability) than the CPS estimates, the opportunity for the small States to borrow strength from the large States through the regression model used for regression and shrinkage estimates is diminished. Part of this effect is due to the absolute loss in precision for the largest States and part to the relative loss in precision compared to the other States, The latter causes the largest States to have less influence on the fitted regression model. Third, because the SIPP estimates would be less precise than the CPS estimates, the shrinkage estimator would weight the direct sample estimate relatively less heavily than the alternative (regression) estimate, and some of the reduction in nonsampling error would be lost for the largest States. Thus, the effect on overall accuracy, as reflected in both sampling and nonsampling error, is ambiious, even for the large States.

underlying both methods. The second reason pertains to the computational burden imposed by the methods.

The ratio-correlation technique assumes that the relationships between the criterion variable and the symptomatic indicators are stable, that the regression equation for State poverty levels estimated using census data can be used to estimate State poverty levels for any year until data from the next census are available (usually about two years after the census is taken). The temporal stability assumption underlying the SPREE method is weaker. The estimation algorithm assumes that the census-year relationships between the variable of interest and the associated variables are stable when more recent sample data do not provide contradictory evidence. If sample data reveal that the relationship between poverty status and age (elderly/nonelderly) has changed at the national level since the census, SPREE estimates will reflect that change. However, if it is determined that sample estimates of poverty status by State are not sufficiently precise to serve as control totals, SPREE must assume that the relationship between poverty status and State is stable.

Both the ratio-correlation technique and the SPREE method require census data. Because long-form data from the 1990 census are not yet available, we would have to use 1980 census data for this study.

Income data collected in the 1980 census pertain to 1979, and our objective is to obtain State estimates of poverty and FSP eligibility for 1986, 1987, and 1988. We have no reason, however, to believe that the relevant multivariate relationships have remained stable over time, in general, and over the 1980s, in particular, especially given the length of time that has elapsed between the 1980 census and the years for which State estimates are desired and given known changes in macroeconomic conditions. 1986, 1987, and 1988 were part of a prolonged economic expansion with low inflation and falling unemployment rates. In contrast, very high (doubledigit) inflation prevailed during 1979, and unemployment had already reached its lowest point from which it would begin to rise sharply. As aggregate economic conditions were seemingly improving, however, the national poverty rate rose by about two percentage points between 1979 and 1986-1988. (U.S. Department of Commerce, 1990) With no evidence suggesting that either the ratio-correlation technique or SPREE strongly dominates shrinkage estimators (in terms of, for example, lower sampling error), we believe that it is prudent to avoid potential biases from assuming temporal stability.

We also recommend against the empirical application of the ratio-correlation technique and SPREE because of the computational burdens imposed by these methods. Published census data could not be used to obtain FSP eligibility estimates. FSP eligibility estimates could be obtained from census data only by processing microdata records and simulating FSP eligibility status for individuals or households before aggregating across observations within each State.

We could use the ratio-correlation technique and SPREE to obtain State poverty estimates but not State FSP eligibility estimates. This approach would avoid the FSP eligibility simulations. Use of census microdata would be avoided entirely with the ratio-correlation technique because State poverty estimates from the census are published and readily available. Use of census microdata would also be avoided entirely with the SPREE method if poverty status were published by a satisfactory set of associated variables. Published 1980 census volumes cross-tabulate poverty status by State by race by age by receipt of social security, for example. We would recommend further consideration of the SPREE method for obtaining State poverty estimates in future research.

III. PRELIMINARY EMPIRICAL ISSUES

This chapter discusses several issues that must be resolved before we obtain State estimates of poverty, FSP eligibility, and FSP participation. Section A discusses whether the unit of analysis should be the individual, the family, or the household We choose the individual as our unit of analysis. Section B descrii our method for determining the poverty status of individuals in the CPS, and Section C descrii our method for determining the FSP eligibility status of individuals in the CPS. Section D describes how we measure FSP participation and correct for issuance errors.

A. UNIT OF ANALYSIS

The official definition of poverty is based on the total income of a family. In contrast, FSP eligibility criteria consider the total income and assets of a household, which may consist of more than one family. Although poverty is a family concept and FSP eligibility is a household concept, both poverty and FSP eligibility are well defined at the individual level. If a family is in poverty, all members of the family are in poverty. If a household is eligiile for the FSP, all members of the household are eligible for the FSP. Because both poverty and FSP eligibility are well defined at the individual level, we use the individual as our unit of analysis. This also eliminates the problem of comparing counts expressed in different units: counts of families in poverty and counts of households eligiile for the FSP. In this study, a poverty count is the total number of individuals in families below the poverty line, and an FSP eligibility count is the total number of individuals in households eligible for the FSP.

Another reason for counting individuals rather than families or households pertains to the availability of administrative records data for the regression and shrinkage estimation methods. The auxiliary data required by these estimation methods are more readily available at the individual level. For example, the Social Security Administration reports the number of individuals receiving Supplemental Security Income (SSI) but not the number of families or households with SSI recipients. Administrative records data on the number of households with Aid to Families with Dependent Children (AFDC) recipients are also unavailable. Although a symptomatic indicator could, in principle, be in different units from the criterion variable, a regression model with the criterion variable and the symptomatic indicators in the same units (either individuals, families, or households) avoids confounding the association between the criterion variable and a symptomatic indicator with variations among States in average family or household sizes.

B. DETERMINING POVERTY STATUS IN THE CPS

We use the same procedure as the Census Bureau for determining which individuals in the CPS were in poverty. We compare the income of each family in the CPS to a poverty threshold for that family.[1] Persons in each household are classified into four family types: (primary) families, unrelated subfamilies, nonfamily householders (formerly, "primary individuals"), and secondary individuals age 15 or over.[2] For families with an income to poverty threshold ratio below 1.0, all individuals in the family are determined to live in poverty. Like the Census Bureau, we exclude unrelated (secondary) individuals under age 15 from our poverty estimates.[3] No income data are collected for these persons.

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[1]The poverty threshold is a data field on family records on the CPS tape. Poverty thresholds depend on family size, number of children, and age of the family householder. The guidelines are updated every year to reflect changes in the consumer price index. In 1988, the average poverty threshold for a family of four was $12,092. Our procedure for determining poverty status uses the poverty definition adopted for official government statistical use by the Office of Management and Budget_

[2]Persons in related subfamilies are members of the primary family.

[3]In Chapter V, we present estimates of State poverty rates and State FSP eligibility rates. We obtain a State rate by dividing a State count-the number of individuals in poverty or eligible for the FSP-by the State population. For calculating rates, we exclude from the State population total secondary individuals under age 15 living in households.

C. DETERMINING FSP ELIGIBILITY STATUS IN THE CPS

In this study, we use a simple procedure to impute FSP eligiiility status for individuals in the CPS. Food stamp program rules are quantified and applied to each household in the CPS to determine the household's eligibility status. Each individual in an eligible household is determined to be eligible for the FSP. We determine eligibility status for August of each year![4]

For this study (and the years 1986 to 1988), a CPS household is determined to be eligible for the FSP if its assets are less than $2,000 ($3,000 for elderly households), its monthly gross income does not exceed 130 percent of the monthly federal poverty guidelines (a test that is applicable only if there are no elderly or disabled persons in the household), and its net income does not exceed monthly federal poverty guidelines.[5] Households in which all members receive public assistance are automatically eligible.

The CPS does not provide monthly income figures and does not contain information on the food stamp unit or asset holdings. We allocate annual income amounts to months using the procedures described in Appendix A The official food stamp unit definition requires shared food purchases and preparation in addition to shared living quarters for a group of individuals to be a food stamp unit. Because the CPS does not provide information on food purchase and preparation, the unit of eligiiility used in this study is the census household minus SSI recipients in States (California and Wisconsin) that issue cash in lieu of food stamp coupons. We calculate gross income from the estimated total monthly income of all members of the household and impute net income from the household's earnings, unearned income, and geographic location using an estimated regression

[4]As we note in Chapter V, national eligibility counts estimated from the CPS are higher than national eligibility counts estimated from SIPP, with which we can more accurately determine FSP eligibility status. However, SIPP data are not appropriate for obtaining State estimates, as noted in Chapter II

[5]The official monthly poverty guidelines are published by the U.S. Department of Health and Human Services and are adjusted each year to account for inflation. The FSP income guidelines based on the poverty guidelines are the same for the 48 contiguous states and the District of Columbia but vary slightly for Alaska and Hawaii and U.S. territories. Like the poverty guidelines, the FSP income guidelines depend on household size.

equation. We estimate assets by dividing the reported income from financial assets in each household by a rate of return of 6.5 percent. Appendix A describes these procedures in greater detail.

D. MEASURING FSP PARTICIPATION

We do not have to rely on sample survey data to estimate FSP participation counts by State. Instead, we use State program operations data, which give population counts of FSP participants in each State. Such estimates are not subject to sampling error.[6] The program operations data are recorded monthly. For this study focusing on interstate variations, we could use data from any month. We use the August participation counts in each year because the data needed for the FSP eligibility simulations pertain to August.

The program operations data record the number of persons in households that received food stamps. Because we want to estimate a State's participation rate--the ratio of the number of participants to the number of eligibles-we may wish to adjust for errors in issuance, that is, remove from the total number of participants the number of individuals who received food stamps but were not eligible. Issuance error estimates are obtained from samples of cases drawn by the States. Thus, some sampling error is introduced by adjusting the participation figures for errors in issuance. We received State estimates of issuance errors for 1986, 1987, and 1988 from FNS. A State estimate gives the proportion of participants that are ineligible. Multiplying the unadjusted participation count by one minus this proportion ineligible gives the adjusted participation count for the State.

[6]Trippe (1989) discusses the relative advantages and disadvantages of survey and program operations data for measuring FSP participation. For this study, the absence of sampling error is the primary reason for our using program operations data.

IV. ESTIMATION PROCEDURES

This chapter describes our estimation procedures for obtaining State estimates of poverty, FSP eligibility, and FSP participation. Sections A, B, and C describe our estimation procedures for the direct sample estimation method, the regression method, and shrinkage methods, respectively. Each section discusses how we obtain State estimates and how we measure the precision of those estimates.

A. DIRECT SAMPLE ESTIMATION

Our direct sample estimates are obtained from the March CPS for 1987, 1988, and 1989. Therefore, our estimates pertain to 1986, 1987, and 1988. The following two sections describe how we calculate direct sample estimates of poverty, FSP eligibility, and FSP participation and how we measure the precision of those estimates.

1. The Direct Sample Estimator

To obtain direct sample estimates of State poverty counts or FSP eligibility counts, we sum the population weights for individuals determined to be in poverty or eligible for the FSP using the methods described in Chapter III. We obtain direct sample estimates of State poverty rates and FSP eligiiity rates by dividing for each State the direct sample estimates of the poverty count and FSP eligibility count by the State population.

2. Measuring the Precision of Direct Sample Estimates

We calculate standard errors for our direct sample estimates of poverty and FSP eligiiility using the Census Bureau's generalized variance functions.[1] To derive the standard error for a CPS estimate of a State poverty or FSP eligibility count, we use the following generalized variance function:

[1]Wolter (1985) discusses the specification, estimation, and limitations of generalized variance functions.

$$\text{(IV.1)} \qquad s_x = \sqrt{f^2 a x^2 + f^2 b x}\ ,$$

where s_x is the standard error of the estimated State count, f^2 is a State-specific generalized variance function parameter, a and b are the generalized variance function parameters pertaining to poverty estimates, and x is the estimated State count (the number of individuals in the State who are in poverty or are FSP eligible). The Census Bureau provides estimated values for all the a's, b's, and f^2's in the CPS technical documentation. To derive the standard error for a State poverty or FSP eligiiility rate estimate, we use the following generalized variance function:

$$\text{(Iv.2)} \qquad s_{x,p} = \sqrt{\frac{f^2 b}{P}\, p\ (100 - p)}\ ,$$

where $s_{x,p}$ is the standard error of the estimated rate (written as a percentage), p is the estimated poverty or FSP eligibility rate (written as a percentage), P is the base of this estimated poverty or FSP eligiiility rate (the State population), and b and f^2 are defined as before.

One problem with using the generalized variance functions is that our FSP eligiiility estimates are not true direct sample estimates because we must simulate FSP eligibility status. Therefore, our estimated standard errors may not be reliable. Although our simulation procedure may reduce sampling variability, it may introduce nonsampling error. Assessing the effects of simulating FSP eligibility status on standard errors of FSP eligiiility estimates is beyond the scope of this study. Thus, we assume that our FSP eligibility e&mates are direct sample estimates. Estimated standard errors should be interpreted with caution.[2]

[2]Because the shrinkage estimator that we use in this study and describe later in this chapter relies on the estimated standard errors of our direct sample estimates, we determine in Chapter V whether our shrinkage estimates are substantially different when we assume that the true standard errors of our direct sample estimates are 20 percent higher than the estimated values. This is a reasonable sensitivity test, although we cannot be sure that the estimated standard errors understate the true standard errors.

A second problem with using the generalized variance functions is that, even if our FSP eligiiility estimates were true direct sample estimates, the generalized variance functions that we use pertain to poverty estimates. However, it does not seem that this could be an important source of error in our estimated standard errors for FSP eligibility estimates, given the similarities in poverty guidelines and FSP eligibility income guidelines.

A third problem with using the generalized variance functions is that the estimated standard errors of rates and counts are inconsistent. The standard error of a State's poverty rate multiplied by the State's population should equal the standard error of the State's poverty count.[3] The Census Bureau's procedure for estimating generalized variance function parameter values does not ensure that this equality will be satisfied. In fact, we find that the standard error for a count derived indirectly from the standard error for a rate is about seven to eight percent lower in the typical State than the standard error derived directly from the generalized variance function for a count. We are concerned about this inconsistency because, for reasons given in Sections B and C, we must specify our regression and shrinkage models in terms of rates. Then, we must obtain count estimates and count standard errors from the rate estimates and rate standard errors. In selected tables in Chapter V, we report standard errors of direct sample estimates of counts derived directly using the generalized variance function for count estimates (Equation (IV.l)). However, when we compare estimates obtained from different methods, we rely on standard errors of direct sample estimates of counts derived indirect& using the generalized variance function for rate estimates (Equation (IV.2)). In most tables in Chapter V, we report the standard errors derived indirectly.

[3]A standard result from statistics is that, if p is a random variable, P is a constant, and $x = Pp$, then the standard error of x is P times the standard error of p. Here, p is the State poverty rate, P is the State population, and x is the State poverty count. Because a CPS State population estimate is not subject to sampling error, it can be treated as a known constant. [For each State, CPS population weights sum to a population estimate derived from nonsample (census and administrative records) data.] Strictly, some sampling error is introduced by subtracting a sample estimate of unrelated individuals under age 15 from the State population total to obtain the total used.

We calculate standard errors for estimated poverty and FSP eligiiility counts and rates using Equations (IV.1) and (IV.2). To calculate a standard error for a State FSP participation rate estimate, we use the following expression:

$$(IV.3) \qquad s_T = \frac{T\,(1 - i)}{G} \sqrt{\frac{i}{(1 - i)\,n} + \frac{s_G^2}{G^2}},$$

where s_T is the standard error of the estimated participation rate, T is the unadjusted participation count, i is the issuance error rate (the proportion of participants who are ineligible), G is the estimated eligibility count, so is the standard error of G, and n is the sample size on which the estimate of i is based. Although some States estimate i from a stratified sample of case files, we assume that i is estimated from a simple random sample of size n. The first term under the radical captures the contribution of sampling error in i to the standard error of the adjusted participation count. Because we find that this contribution is very small relative to the contribution of sampling error in our FSP eligibility count estimate, we do not take into account the effects of the more complex sampling schemes used by some States to estimate issuance error rates.[4] For this report, we derive so using the indirect method described earlier. Equation (IV.3) gives a Taylor series approximation to the standard error of a ratio estimated from a sample drawn under a complex design, such as the CPS design (Wolter, 1985).[5] Exact expressions for standard errors of ratios cannot generally be obtained. We also use Equation (IV.3) to calculate standard errors for regression and shrinkage estimates of FSP participation rates, using regression and shrinkage estimates of G and s_G

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[4]Also, information on State sampling schemes is not readily available. FNS supplied values of n for all States.

[5]A participation rate is a ratio, the ratio of the number of participants to the number of eligibles.

B. THE REGRESSION METHOD

The objective of the regression method is to smooth direct sample estimates and reduce sampling variability. The following sections describe our estimation procedures for applying the regression method and discuss issues that arise in obtaining regression estimates.

1. The Regression Model and Estimator

The regression method is a model-based approach to small-area estimation. The general form of the regression model is:

$$\text{(IV.4)} \quad Y = XB + u.$$

For this study, Y, the criterion variable, is a (51 × 1) vector of State-level sample (CPS) estimates measuring the incidence of poverty or FSP eligibility. X is a (51 x p) matrix containing data for each State on a set of p − 1 symptomatic indicators.[6] B is a (p × 1) vector of parameters to be estimated. u is a (51 x 1) vector of disturbances reflecting the inability of the symptomatic indicators to account for all of the interstate variation in poverty or FSP eligibility and the fact that the sample estimates of poverty or FSP eligibility are subject to sampling error. We assume that the elements of u have means equal to zero and the same (unknown) variance and that the elements of u are statistically independent. Because our model fitting procedure will be guided by "t-statistics" indicating whether individual elements of B are significantly different from zero and, therefore, whether the corresponding symptomatic indicators are related to the incidence of poverty or FSP

[6]One of the p columns in X is for a constant term (intercept) taking a value of one for all States.

eligibility, we will also assume that the elements of u are normally distributed.[7] The regression method can be used to obtain small-area estimates without assuming normally distributed errors.[8]

The regression estimator is:

$$\text{(IV.5)} \quad \hat{Y} = X\hat{B}.$$

$\hat{B}$ is our estimate of B. We obtain $\hat{B}$ by ordinary least squares (OLS).

2. Criterion Variables and Symptomatic Indicators

Our criterion variables are direct sample estimates measuring the incidence of poverty and FSP eligiiility at the State level. For both poverty and FSP eligibility, we consider two measures of incidence. One measure is the State count, the number of individuals in poverty or the number of individuals eligible for the FSP. The other measure is the State rate, the proportion of individuals in the State who are in poverty or the proportion of individuals in the State who are eligible for the FSP. Although we eventually want to obtain estimates of State counts, we estimate regression models for State rates. The reasons for expressing criterion variables as rates rather than counts are explained in section 4. We do not use the FSP participation rate as a criterion variable. Instead, we derive regression estimates of FSP participation rates by dividing participation counts adjusted for

[7]Because a State poverty count cannot be negative, the ranges of the elements of Y and, thus, the elements of u are restricted Although a normal random variable is unbounded, we have no reason to suppose that the distributions of the elements of u are not approximately normal. Normality is a standard assumption.

[8]Although we assume normality so that we can identify a "best" regression model, the calculations performed to obtain regression estimates from a given model are the same with or without the normality assumption.

issuance errors by regression estimates of FSP eligibility counts.[9] The derivation of the sample estimates of poverty and FSP eligibility used as criterion variables was described in Section A.

For this study, there are several necessary or, at least, desirable properties for estimates of a symptomatic indicator. These properties include the availability of estimates for every State, the availability of estimates on an annual basis, and the availability of estimates soon after the year to which the estimates pertain. We also argued in Chapter II that estimates of symptomatic indicators should have little or no sampling variability. Symptomatic indicators should, of course, be associated with the criterion variable under consideration.

Our preliminary list of potential symptomatic indicators satisfying these properties is as follows:

- The proportion of individuals in the State receiving Aid to Families with Dependent Children (AFDC)
- The proportion of individuals in the State receiving Supplemental Security Income (SSI)
- State per capita total personal income
- The State crime rate (the number of violent and property crimes per 100,000 population)
- Low birthweight births (less than 2,500 grams) as a proportion of all live births in the State
- A dummy variable equal to one if one percent or more of the State's total personal income is attributable to the oil and gas extraction industry

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[9]The purpose of the regression method is to smooth direct sample estimates and reduce sampling variability. If we did not adjust participation counts for issuance errors, the only source of sampling variability in a participation rate estimate would be the eligiiility count estimate, which is the denominator of the participation rate. (Our participation count from program operations data, which is the numerator of the participation rate, is a population, not sample, estimate.) Using regression estimates of eligibility counts to obtain participation rate estimates would give smoothed participation rate estimates. The only additional source of sampling variability that arises in this study and remains to be smoothed is attributable to our adjusting participation counts for issuance errors and to the sampling variability in issuance error estimates. We do not believe, however, that interstate variations in issuance error rates could be successfully modeled without a much greater knowledge of the causes of issuance errors and the availability of a wider array of symptomatic indicators.

Sources for the estimates of these symptomatic indicators are given in Appendix B. The dummy variable for oil and gas income was identified and added to the list of potential symptomatic indicators only after we had fit several preliminary regression models for poverty in 1988 and discovered a strong pattern among the residuals.[10] Alaska, Colorado, Louisiana, New Mexico, Oklahoma, and Texas had consistently higher poverty rates than predicted on the basis of the other symptomatic indicators.

3. The Model Fitting Procedure

For each of the three years (1986, 1987, and 1988) and each of the two criterion variables (poverty rate and FSP eligibility rate), we use a simple procedure adopted by Ericksen and Kadane (1987) to select the "best" set of symptomatic indicators and the "best" regression model.[11] The procedure identifies the best one-variable model, the best two-variable model, the best three-variable model, and so forth. The best three-variable model is the three-symptomatic-indicator model with the highest R^2 and with t-statistics greater than two for all three symptomatic indicators. R^2 is the coefficient of multiple determination. It lies between zero and one, inclusive, and gives the proportion of the interstate variation in the criterion variable that is "explained" by the symptomatic indicators. A t-statistic equals the estimated coefficient for a symptomatic indicator divided by the coefficient's estimated standard error. If the t-statistic is greater than two, we are 95 percent confident that the coefficient is different from zero and that the symptomatic indicator is associated with the criterion variable (the symptomatic indicator and its coefficient are "significant"). For this study, we also explicitly added the condition that the sign of each significant coefficient "make sense."

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[10]A residual is the difference between the observed value of the criterion variable and the predicted value of the criterion variable. In our notation, the vector of state residuals is given by $Y - \hat{Y}$.

[11]This model fitting procedure would not be appropriate if our objective were to test behavioral hypotheses rather than to smooth direct sample estimates.

We believe that higher per capita income should be associated with lower poverty, for example Thus, the coefficient on per capita income should he negative.

If, for example, we do not fmd a four-variable model with t-statistics greater than two for all four symptomatic indicators, we select the beat overall regression model from among the best one-variable, the beat two-variable, and the best three-variable models.[12] To determine whether the best three-variable model is better than the best two-variable model, we compare the explanatory power of the models to assess the gain from adding a third variable. We cannot rely on R^2 for this comparison. If R^2 is less than one, adding a symptomatic indicator will always increase R^2, and our best overall model would always be the three-variable model. Whether the gain from adding a third variable is substantial is partly a subjective judgment, a judgment that may be made easier by considering adjusted measures of R^2 that penalize the addition of variables.[13] We return to this issue in Chapter V, when we discuss our empirical results.

4. Specification of the Criterion Variable

Our specification of the basic regression model assumes that the variance of the error term u is the same for each State. However, a common problem is to find unequal error variances when the units of observation in a regression--States, in this study-have very different sizes. Although size can

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[12]It is possible for a four-variable model with t-statistics greater than two for all four symptomatic indicators to have a lower R^2 than either the beat three-variable model or another four-variabk model with at least one t-statistic less than two. For ease of exposition, we ignore this case. Regardless, we would not regard such a model as the best overall. (For a four-variable model to have a lower R^2 than a three-variable model, the four-variable model must have at least two symptomatic indicators that do not appear in the three-variable model.)

[13]Amemiya (1985) discusses two adjusted measure of R^2. One is $\bar{R}^2 = 1 - [51/(51 - p)](1 - R^2)$. The other, which penalizes the addition of variables more heavily, is $\tilde{R}^2 = 1 - [(51 + p)/(51 - p)](1 - R^2)$. p − 1 is the number of symptomatic indicators.

be measured in different ways, California is at least 60 times larger than Wyoming if size is measured by population, the poverty count, or the FSP eligibility count.[14]

In preliminary regressions using the poverty count or the FSP eligiiility count as the criterion variable, we found strong evidence of unequal error variances. This condition is called "heteroskedasticity."[15,16] The consequence of heteroskedasticity is that, using OLS, we cannot assess the overall fit of the regression model or the significance of individual symptomatic indicators. Thus, our model fitting procedure will fail. Our inability to assess the fit of the regression model and to identify a "best" regression model also implies that we cannot calculate the shrinkage estimates described in Section C.

Ericksen (1974) recommends specifying the criterion variable as a rate rather than as a count--the poverty rate rather than the poverty count, for example-as a way to equalize error variances across States.[17] A State poverty rate or FSP eligibility rate is obtained by dividing the State poverty count or FSP eligibility count by the State population. In our regressions using the poverty rate or the FSP eligiiility rate as the criterion variable, we find no statistically significant evidence of heteroskedasticity. Thus, unless otherwise noted, all regression results reported in this study pertain

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[14]We expect the poverty count and the FSP eligibility count to be strongly positively correlated with population. For 1988, both estimated correlations based on direct sample estimates equal 0.96.

[15]Our test for heteroskedasticity was proposed by Breusch and Pagan (1979). The basic idea of their test in the context of this study is, roughly, that the residuals from an OLS regression should not be significantly related to state population size or any other variable if there is no heteroskedasticity. If, on the other hand, error variances are larger in larger states, for example, residuals should be larger in larger states. The Breusch-Pagan test is described in detail in Judge et al. (1980).

[16]We estimated many different regression models in which the criterion variable was the poverty count or FSP eligibility count. In each case, the hypothesis that error variances are equal across states could be rejected at any conventional level of significance.

[17]Ericksen (1974) also notes that the distribution of rates is often more normal and less skewed than the distribution of counts. That is true for this study.

to models in which the poverty rate or the FSP eligibility rate is the criterion variable.[18] Estimates of counts are derived indirectly from regression estimates of rates by multiplying the rate estimates by State population totals

5. Measuring the Precision of Regression Estimates

The purpose of the regression method is to smooth direct sample estimates and obtain estimates with lower sampling variability. Reductions in sampling variability are evidenced by smaller standard errors. Standard errors of regression estimates can be easily estimated.[19,20]

As we noted in Chapter II, the cost of obtaining lower sampling variability is bias. In contrast to direct sample estimates, regression estimates are biased. Thus, to compare the precision of direct sample estimates and regression estimates, we prefer a measure of precision that accounts for not only sampling error but also bias. One such measure is mean square error (MSE).

In applications where the objective is to estimate a single value, the MSE of an estimator is the bias squared plus the variance. The variance is the standard error squared. For this study, in which

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[18]An alternative approach would have been to specify the criterion variables as counts and to estimate the regression models by generalized least squares (GLS) rather than OLS. GLS accommodates heteroskedasticity. However, using GLS would have required our making assumptions about how error variances vary among states and our specifying the form of the heteroskedasticity. Regression estimates may have been sensitive to the specification chosen, and a careful sensitivity analysis would have been beyond the scope of this study. The GLS approach also would have complicated the shrinkage estimator proposed in Section C.

[19]The estimated variance-covariance matrix of the regression estimator is $s_u^2 X(X'X)^{-1}X'$, where $s_u^2 = [(Y - \hat{Y})'(Y - \hat{Y})]/(51 - p)$ is the sum of squared residuals divided by $51 - p$. Standard errors of the 51 state regression estimates are given by the square roots of the diagonal elements of the (51×51) variance-covariance matrix. Because the criterion variable in our regression is specified as a rate, these standard errors pertain to regression estimates of rates. To obtain a standard error for a count estimate, we multiply the standard error for the rate estimate by the State population total.

[20]As noted earlier, we do not fit regression models with the FSP participation rate as the criterion variable+ Our regression estimates of FSP participation rates are derived from our regression estimates of FSP eligibility counts (which are obtained from regression estimates of eligibility rates). We calculate standard errors for our regression estimates of FSP participation rates using Equation (IV.3) in Section A.

51 estimates are required, the MSE is represented by a matrix.[21] Although we have derived an analytical expression for the MSE matrix, the MSE matrix of the regression estimator is not estimable. Moreover, it is not possible to determine whether the regression estimator is better (or worse) in terms of MSE than the direct sample estimator.[22,23]

C. SHRINKAGE METHODS

Our objective in applying shrinkage methods is to combine direct sample estimates and regression estimates to exploit optimally the unbiasedness of direct sample estimates and the lower sampling variability of regression estimates. Shrinkage estimators can take many forms, including different kinds of James-Stein estimators, Bayes estimators, and Empirical Bayes estimators. For this study, we choose a specification used for small-area estimation by Ericksen and Kadane (1985, 1987). The Ericksen-Kadane estimator, originally developed by DuMouchel and Harris (1983) based on pioneering work by Lindley and Smith (1972), is a hierarchical Empirical Bayes estimator. Ericksen and Kadane used this estimator to obtain estimates of population undercount in the 1980 census for 66 local areas constituting the entire United States.

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[21]The MSE matrix is (51 x 51). The 51 diagonai elements are the squared estimation errors for the 51 States. Each off-diagonal element captures any tendency for the estimation errors in two different States to be related. For example, a positive value for the (1,2) cell in the MSE matrix indicates that, if the regression estimate for the first State is too high, the regression estimate for the second State is also probably too high.

[22]Amemiya (1985) defines "better" precisely.

[23]Comparing two matrices--each with ($51^2 =$) 2,601 elements-is harder than comparing two single numbers. Scalar (single-number) approximations are available for measuring the "size" of a matrix_ One is the matrix trace, which is the sum of the diagonal elements of the matrix Ericksen (1974) finds, however, that estimates of this measure can be highly sensitive to underlying parameter estimates and may not be reliable. Moreover, the estimates obtained cannot strictly be interpreted to support an inference of how much better or worse the regression estimator is compared to the direct sample estimator. For these reasons, we do not calculate approximate MSE estimates for the regression estimator.

1. The Shrinkage Model and Estimator

Because Ericksen and Kadane (1985, 1987) describe their hierarchical Empirical Bayes model in detail and develop the intuition for the Bayesian framework, we will only summarize the model's basic features for this report. The first level of the hierarchy is a probability model describing the sampling distribution of the direct sample estimator. The model specifies the means and standard errors of the direct sample estimates. Because the direct sample estimator is unbiased, the means are the true (unknown) values measuring the incidence of poverty or FSP eligibility. The second level of the hierarchy is a regression model. In this study, the regression model relates poverty or FSP eligibility to symptomatic indicators and captures systematic factors associated with interstate differences in poverty or FSP eligibility.

Our shrinkage estimator is:

(IV.6) $\quad d = (D + s^{-2}P)^{-1}DY,$

where d is a (51 x 1) vector of shrinkage estimates of poverty or FSP eligibility, and Y is a (51 x 1) vector of direct sample (CPS) estimates of poverty or FSP eligibility. D is a (51 x 51) diagonal matrix with diagonal element (i,i) equal to one divided by the variance (standard error squared) of the direct sample estimate for State i $P = I - X(X'X)^{-1}X'$ is a (51 x 51) matrix, where I is a (51 x 51) identity matrix (all diagonal elements equal one, and all other elements equal zero) and X is a (51 x p) matrix containing data for each State on a set of p − 1 symptomatic indicators. This is the same X matrix used by the regression method. $s^{-2} = 1/s^2$, where s^2 is a scalar representing the interstate variability in poverty or FSP eligibility not explained by the symptomatic indicators. Thus, s^2 reflects the lack of fit of the regression model. We estimate s^2 by maximizing the following likelihood function with respect to s:

(IV.7) $\quad L = |W|^{1/2}\,|X'WX|^{-1/2}\exp[-\tfrac{1}{2}Y'SY],$

where $W = (D^{-1} + s^2I)^{-1}$ and $S = W - WX(X'WX)^{-1}X'W$. $|W|^{1/2}$ is the determinant of the matrix W raised to the one-half power (the square root of the determinant of W). exp[ ] is the exponentiation operator (e = 2718231828.. raised to the power given by the number in brackets).

Although the analytical expression for our shrinkage estimator is complicated, at least one intuitively sensible implication can be seen easily. If our symptomatic indicators explain none of the interstate variability in poverty or FSP eligibility, then $s^{-2}P = 0_{51}$, where 0_{51} is a (51 X 51) matrix of zeros. $s^{-2}P = 0_{51}$ implies $d = D^{-1}DY = Y$. Thus, when the regression model has no explanatory power, no weight is given to the regression estimates, and the shrinkage estimates equal the direct sample estimates.

Because the criterion variables in our regression models are specified as rates rather than as counts (for reasons given in Section B), our shrinkage estimator produces estimates of rates. Estimates of counts can be easily obtained from estimates of rates. We estimate a State poverty count by multiplying the State's estimated poverty rate by the State population.

2. Measuring the **Precision of Shrinkage Estimates**

The variance-covariance matrix of our shrinkage estimator is:

(IV.8) $$V = (D + s^{-2}P)^{-1},$$

where D, s^{-2}, and P are as defined before." Standard errors of the 51 State shrinkage estimates are given by the square roots of the diagonal elements of V, a (51 x 51) matrix.[25,26]

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[24]The "final answer" from a Bayesian analysis is a *distribution* for the true values that we are trying to estimate. The distribution is conditional on the observed data (sample estimates and symptomatic indicators in this study). Our shrinkage estimator, d, is the mean of such a distribution, and V is the variance-covariance matrix of the distribution. Given certain assumptions, which were made by DuMouchel and Harris (1983) and Ericksen and Kadane (1985) and which we also make, the distribution is normal. The distribution characterizes the uncertainty that remains after the observed data are taken into account.

[25]These standard errors pertain to estimates of poverty rates or FSP eligibility rates. **To obtain** estimated standard errors for poverty counts or FSP eligibility counts, we multiply the rate standard error for each State by the State's total population.

If our shrinkage estimator gives any weight to the regression estimates, the shrinkage estimator is biased. It would be desirable, therefore, to measure the precision of our shrinkage estimator using the MSE criterion. However, because an estimable analytical expression for the MSE matrix of our shrinkage estimator is not available, we do not report MSE estimates.

[26]Our shrinkage estimates of FSP participation rates are derived from our shrinkage estimates of FSP eligibility counts. We calculate standard errors for our shrinkage estimates of FSP participation rates using Equation (IV.3) in Section A

V. EMPIRICAL RESULTS

This chapter presents results from our empirical application of the direct sample estimation method, the regression method, and the chosen shrinkage method. We determine the poverty and FSP eligibility status of individuals in the CPS as descrii in Chapter III and use the estimation procedures descrii in Chapter IV. We obtain direct sample, regression, and shrinkage estimates of poverty, FSP eligibility, and FSP participation. Section A presents our direct sample estimates. Section B describes the results from our application of the regression model fitting strategy discus& in Chapter IV and presents our regression estimates. Section C presents our shrinkage estimates. Our shrinkage estimator is the hierarchical Empirical Bayes estimator described in Chapter IV. Each of these three sections discusses our estimates of State poverty counts, poverty rates, eligibility counts, eligibility rates, and participation rates and examine the precision of the estimates obtained. Section D assesses the three alternative estimators based on our empirical results. Our assessment focuses on the similarities and differences in the distributions of States estimates, in the point estimates for individual States, in the precision of estimates, and in the interval estimates (confidence intervals) for individual States. We also assess the relative sensitivity of alternative estimates to model specification, for example.

A. DIRECT SAMPLE ESTIMATES

This section presents our direct sample estimates of State poverty counts, State FSP eligibility counts, and State FSP participation rates. It also presents our direct sample estimates of State poverty rates and State FSP eligibility rates.

1. Direct Sample Estimates of State Poverty Counts

Table V.1 displays direct sample estimates of State poverty counts-the number of individuals in poverty-for 1986, 1987, and 1988. Table V.l also gives standard errors for the estimated counts.

We derive the standard errors by multiplying the standard errors of estimated poverty rates by State population totals. States are grouped according to the nine census divisions, although we do not derive estimates for divisions. Each United States total is the sum of the 51 State counts.[1]

Because the poverty count is so strongly correlated with State population size, the implications of estimated counts are difficult to assess. In most cases, one State has a higher poverty count than another State because it has more residents. According to Table V.l, 31,745,000 individuals were in poverty in 1988 in the entire United States. Estimated State poverty counts for 1988 range from 43,000 individuals in Wyoming and Vermont, the smallest and third smallest States, to 3,687,000 individuals in California, the largest State. The median State poverty count estimate for 1988 is 457,000 individuals for Maryland.

Although it may be hard to compare estimated poverty counts for States of different sizes, it is easy to see that many of the standard errors of the direct sample estimates are very large relative to the estimated counts. In Table V.l, the standard error is more than ten percent of the estimated 1988 poverty count for 39 States. The standard error is more than 15 percent of the estimated count for 20 States and more than 20 percent of the estimated count for 4 States. In one of those three States, Connecticut, the standard error is about 30 percent of the direct sample estimate. Using the ratio of the standard error to the estimated count as a standard of precision, we find that the direct sample estimate for Texas is the most precise. For Texas, the standard error is about 5.9 percent as large as the poverty count for 1988. The 95 percent confidence interval for Texas' poverty count,

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[1]After submission of the first draft of this report, the Census Bureau published for the first time ever CPS estimates of State poverty counts and poverty rates. The published estimates, pertaining to the years 1980-1990, are direct sample estimates obtained from the March CPS. The direct sample estimates contained in this report match those published for 1986 and 1988. This report's estimates for 1987 are based on a data file created under the Census Bureau's former CPS data processing system and do not agree exactly with the published figures, which are based on a file created under the current processing system. The current processing system was implemented between the March 1988 CPS and March 1989 CPS, although a March 1988 CPS file was later created under the new processing system. The direct sample estimates published by the Census Bureau are accompanied by the warnings that they "should be used with caution since relatively large standard errors are associated with these data" and "we advise strongly against using these estimates to rank the States" (U.S. Department of Commerce, 1991).

however, is still the second widest at nearly 690,000 persons.[2] We are 95 percent confident that Texas' 1988 poverty count was between 2,661,000 and 3,351,000 individuals. California has the widest 95 percent confidence interval at over 1,000,000 persons. Using the direct sample estimation method, we are 95 percent confident that California had between 3,179,000 and 4,195,000 poor people in 1988.

2. Direct Sample Estimates of State FSP Eligibility Counts

Table V.2 displays direct sample estimates of State FSP eligibility counts-the number of individuals eligible for the FSP--for 1986, 1987, and 1988. Table V.2 also gives standard errors for the estimated counts, which we obtain by multiplying the standard errors of estimated FSP eligibility rates by State population totals. Each United States total is the sum of the 51 State counts, As noted before, each individual's eligibility status is determined using the simulation procedure described in Chapter III and Appendix A. The simulation procedure applies the FSP gross and net income and asset tests.

According to Table V.2, 37,333,000 individuals were eligible for the FSP in 1988 in the entire United States? Estimated State FSP eligibility counts range from 49,000 individuals in Wyoming, the smallest State, to 4,097,000 individuals in California, the largest State. The median State FSP eligibility count estimate for 1988 is 487,000 individuals for Colorado.

As with the poverty counts, many of the standard errors of the direct sample estimates of FSP eligibility counts are very large relative to the estimated counts. For 35 States, the standard error exceeds ten percent of the estimated count for 1988. The standard error exceeds 15 percent of the estimated count for 13 of those States.

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[2]The lower bound of a 95 percent confidence interval is the point estimate (the estimated poverty count) minus 1.96 times the standard error. The upper bound is the point estimate plus 1.96 times the standard error.

[3]The national totals for 1986 and 1988 are similar to the estimates reported by Trippe, Doyle, and Asher (1991). Trippe, Doyle, and Asher (1991) did not derive an estimate for 1987.

We should caution that, because we simulate FSP eligiiility status, our standard error estimates may not be reliable. Within the scope of this study, we cannot judge the effects of the simulation procedure on the precision of our estimates. Although the simulation procedure may smooth out some sampling variability, the procedure may int:oduce nonsampling error. To calculate standard errors of FSP eligibility estimates, we assume that the estimated eligibility counts (or rates) are direct sample estimates obtained without simulation. It may be prudent to regard the standard errors on FSP eligibility estimates as lower bounds on the true values.

3. Direct Sample Estimates of State FSP Participation Rates

Table V.3 displays direct sample estimates of State FSP participation rates-the percentage of FSP-eligible individuals receiving food stamps-for 1986, 1987, and 1988. Table V.3 also gives standard errors for the estimated participation rates. Participation counts are adjusted for errors in issuance. We derive the standard errors in Table V3 from the standard errors in Table V.2. To calculate the standard errors for adjusted participation rates, we assume that the estimates of issuance errors are obtained from simple random samples within each State. Chapter IV describes our procedure for estimating standard errors of participation rates.

According to Table V.3, the median FSP participation rate was 43.9 percent in 1986 and 1987 and 46.6 percent in 1988. The national participation rates implied by our State estimates were **47.1 percent, 47.0 percent, and 48.0 percent in 1986, 1987, and 1988, respectively.**[4,5] Delaware and

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[4]Trippe, Doyle, and Asher (1991), who do not adjust for errors in issuance, report national participation rates of 48.8 percent and 493 percent for 1986 and 1988. Our estimates are lower because we adjust each State participation count for errors in issuance.

[5]We estimate participation rates using CPS rather than SIPP data because SIPP, which is not designed for State estimation, provides small sample sizes and supports much less precise sample estimates for some States and because SIPP uniquely identifies only **42** States. However, as we noted earlier, we can more accurately determine FSP eligibility status using SIPP data. National participation rates estimated using SIPP data are about **10 to 15 percentage points higher than** national participation rates estimated using CPS data (See, for example, Doyle (1990).) Underreporting of income and other data limitations in the CPS explain the differences. The CPS overstates eligibility counts (the denominators of participation rates) and, thus, understates

(continued...)

Alaska had the lowest participation rates in 1986 at 28.7 percent Nevada had the lowest participation rate in 1987 at 22.0 percent, and New Hampshire had the lowest participation rate in 1988 at 20.4 percent Pennsylvania, Michigan, and Wisconsin had the highest participation rates in 1986, 1987, and 1988 at 68.9 percent, 69.8 percent, and 76.5 percent, respectively. In each of the three years, about one-third of the States had participation rates below 40 percent, about one-third of the States had participation rates of at least 40 percent but below 50 percent, and about one-third of the States bad participation rates of 50 percent or more. Table V.3 shows that participation rates tended to be relatively high among States in the Middle Atlantic and East North Central census divisions and relatively low among States in the Mountain and, at least in 1986, West North Central census divisions.

Table V3 shows that standard errors for direct sample estimates of participation rates are extremely large. The median standard error is 5.0 percent for 1986, 5.6 percent for 1987, and 5.7 percent for 1988. For 1988, 22 State estimates have standard errors of at least four percent but less than six percent. The 95 percent confidence interval for a State with a standard error of four percent is about 16 percentage points wide, extending 8 percentage points in either direction from the point estimate of the participation rate Only nine States have narrower confidence intervals for 1988. Twenty States have 95 percent confidence intervals that are at least 24 percentage points wide. Using the direct sample estimation method, we are able to state in the most extreme case only that we are 95 percent confident that Connecticut's FSP participation rate was between 30.1 percent and 90.1 percent. The most precise direct sample estimate is for Florida, for which we are 95 percent confident that the State's FSP participation rate was between 29.5 percent and 363 percent, a range of nearly eight percentage points.

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[5](...continued)
participation rates. Although participation rates for individual States may be understated, an important point is that the estimates reported in this study may accurately reflect the degree of interstate variation in participation rates and the relatiousbips between, for example, poverty and participation rates.

Some of the large fluctuations in participation rates between years may be partly explained by sampling error rather than, for example, behavioral changes. According to the direct sample estimates, Connecticut's participation rate fell by 6 percentage points between 1986 and 1987 before rising by about 17 percentage points between 1987 and 1988. Hawaii's participation rate rose by over 4 percentage points before falling by over 10 percentage points. Even for conservative estimates of year-to-year correlations between direct sample estimates, sampling errors are so great that it is not possible to judge these substantively large changes as statistically significant[6]

4. **Direct Sample Estimates of State Poverty Rates**

Table V.4 displays direct sample estimates of State poverty rates-the percentage of individuals in poverty-for 1986, 1987, and 1988. Table V.4 also gives standard errors for the estimated rates. We present poverty rate estimates for two reasons. First, rates are easier to compare than counts across States of unequal population sizes. Second; for technical reasons discussed in Chapter IV, we require direct sample estimates of rates for the regression and shrinkage methods

According to Table V.4, the median poverty rates in 1986, 1987, and 1988 were 12.9 percent, 12.6 percent, and 12.4 percent, respectively. The national poverty rates implied by our State estimates were 13.6 percent, 13.5 percent, and 13.0 percent. New Hampshire had the lowest poverty rate in 1986 at 3.7 percent and in 1987 at 3.4 percent. Connecticut had the lowest poverty rate in 1988 at 4.0 percent. Mississippi had the highest poverty rate in all three years The direct sample estimates for Mississippi are 26.6 percent, 255 percent, and 27.2 percent In 1986, 8 States had poverty rates below 10 percent, 30 States had poverty rates of at least 10 percent but less than 15 percent, 7 States had poverty rates of at least 15 percent but less than 20 percent, and 6 States had poverty rates of 20 percent or higher. The 1987 and 1988 distributions of poverty rates were similar, but among States with poverty rates under 15 percent, more were under 10 percent in 1987 and 1988.

[6]Sample overlap due to the rotation group design of the CPS causes estimates for consecutive years to be correlated.

Table V.4 shows that poverty rates tended to be relatively low among States in the New England census division and relative@ high among States in the East South Central and West South Central census divisions.

According to Table V.4, standard errors for direct sample estimates of State poverty rates are large. The median standard error in each year is 1.7 percent. For 1988, there were 9 States with standard errors under 1 percent, 3 States with standard errors of at least 1 percent but less than 1.5 percent, 28 States with standard errors of at least 15 percent but less than 2 percent, and 11 States with standard errors of 2 percent or more. The 95 percent confidence interval for a State with a standard error of 1.5 percent is about six percentage points wide, extending three percentage points in either direction from the point estimate of the poverty rate. The 95 percent confidence interval for a State with a standard error of two percent is about eight percentage points wide, extending four percentage points in either direction from the point estimate of the poverty rate. For 1988, there are 11 States with 95 percent confidence intervals that wide or wider. All but 12 States have 95 percent confidence intervals that are at least six percentage points wide Using the direct sample estimation method, we are, for example, 95 percent confident that Nebraska's poverty rate was between 62 percent and 14.4 percent and that Mississippi's poverty rate was between 22.5 percent and 31.9 percent.

Substantial sampling variability may explain some of the large year-to-year changes in poverty rates implied by the direct sample estimates.[7] For example, Montana's poverty rate rose by nearly two percentage points between 1986 and 1987 and fell by almost four percentage poink between 1987 and 1988. New Mexico's poverty rate fell by somewhat under two percentage points and then rose by over three percentage points.

'Some estimated fluctuations may be attributable to nonsampling error, specifically to changes in Census Bureau procedures for processing CPS data. These procedures were implemented between the March 1988 CPS and the March 1989 CPS and would affect differences between 1987 and 1988 estimates. Based on comparisons of national estimates, it is likely that the data process@ changes cause an estimated increase in poverty to be smaller or an estimated decrease in poverty to be larger than it otherwise would have been, especially for a State with a large black population.

5. Direct Sample Estimates of State FSP Eligibility Rates

Table V.5 displays direct sample estimates of State FSP eligibility rates--the percentage of individuals eligible for the FSP--for 1986, 1987, and 1988. Table V.5 also gives standard errors for the estimated rates.

According to Table V.5, the median FSP eligiiility rates in 1986, 1987, and 1988 were 15.8 percent, 15.0 percent, and 14.3 percent, respectively. New Hampshire had the lowest FSP eligibility rate in both 1986 and 1987 at 4.9 percent and 5.8 percent, respectively. Connecticut had the lowest FSP eligibility rate in 1988 at 5.6 percent. Mississippi had the highest FSP eligibility rate in all three years. The direct sample estimates for Mississippi are 34.1 percent, 31.9 percent, and 31.0 percent. In 1986, 3 States had FSP eligibility rates below 10 percent, 16 States had FSP eligibility rates of at least 10 percent but less than 15 percent, 22 States had FSP eligibility rates of at least 15 percent but less than 20 percent, and 10 States had FSP eligibility rates of 20 percent or higher. In 1987, 4 States had FSP eligibility rates below 10 percent, 21 States had FSP eligibility rates of at least 10 percent but less than 15 percent, 15 States had FSP eligibility rates of at least 15 percent but less than 20 percent, and 11 States had FSP eligibility rates of 20 percent or higher. In 1988, 4 States had FSP eligibility rates below 10 percent, 27 States had FSP eligibility rates of at least 10 percent but less than 15 percent, 11 States had FSP eligibility rates of at least 15 percent but less than 20 percent, and 9 States had FSP eligibility rates of 20 percent or higher. Although gains of States by the lowest category and losses of States from the highest category were small, the distribution of State FSP eligiiility rates shifted downward within the 10 percent to 20 percent range during the three years. There were 38 States within this range in both 1986 and 1988, yet 27 of the 38 in 1988 had rates below 15 percent, while only 16 of the 38 in 1986 had rates below 15 percent. Table V.5 reveals differences among not only years but also areas. FSP eligibility rates tended to be relatively low among States in the New England census division and relatively high--generally over 20 percent--among States in the East South Central and West South Central census divisions.

According to Table V.5, standard errors for direct sample estimates of State FSP eligiiility rates are large The median standard error for 1986 and 1988 is about 1.9 percent, while the median standard error for 1987 is about 1.8 percent. For 1988, the estimated standard errors are 2 percent or higher for 20 States and 1.5 percent or higher for 39 States. For only 12 States does the 95 percent confidence interval extends less than about three percentage points in either direction from our direct sample estimate of the FSP eligibility rate.

6. Standard Errors of Direct Sample Estimates of State Poverty Counts and State FSP Eligibility Counts

Table V.6 displays alternative standard errors for direct sample estimates of State poverty counts. We have estimated standard errors by two methods, both described in Chapter IV. The "direct" method uses the Census Bureau's generalized variance function for the standard error of a count, The "indirect" method calculates the count standard error for a State by multiplying the rate standard error for the State by the State's total population. The rate standard error is estimated using the Census Bureau's generalized variance function for the standard error of a rate. The indirect method standard errors in Table V.6 are also displayed in Table V.l.

For comparing the precision of estimates from alternative methods, we must rely on indirect method standard errors. However, these standard errors may overstate the precision of the direct sample estimates. Thus, in this section, we compare the indirect method standard errors with the higher direct method standard errors.

It is easy to show algebraically that the indirect method yields lower standard error estimates than the direct method for all States, as confirmed by Table V.6.[8] For all three years, the indirect method

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[8]As displayed in Chapter IV, the direct method standard error is:

$$\sqrt{f^{2}ax^2 + f^{2}bx} = f\sqrt{x(ax + b)} \quad ,$$

(continued...)

standard errors range from about 86 percent of the direct method standard errors to about 98 percent of the direct method standard errors across the 51 States. The indirect method **standard** error is

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[8](...continued)

where x is the State count (poverty or FSP eligibility). Using the indirect method, we derive x by multiplying the State rate, p, by the State population, P. Then, as noted in Chapter IV, the indirect method standard error is the product of P and the standard error of p. If p is written as a proportion rather than as a percentage, this product is:

$$P\sqrt{\frac{f^2 b}{P}\,p\,(1-p)} = fP\sqrt{\frac{b}{P}\frac{x}{P}\left(1-\frac{x}{P}\right)} = f\sqrt{bx\left(1-\frac{x}{P}\right)}\,.$$

The ratio of the direct method standard error to the indirect method standard error is, after canceling the f factors:

$$\sqrt{\frac{x(ax+b)}{bx\left(1-\frac{x}{P}\right)}} = \sqrt{\frac{ax+b}{b\left(1-\frac{x}{P}\right)}} = \sqrt{\frac{ax+b}{b-b\frac{x}{P}}}\,,$$

which, because b is positive, is greater than one if:

$$ax + b > b - b\frac{x}{P}\,.$$

This inequality is satisfied if:

$$ax > -b\frac{x}{P}$$

or, after canceling the x's, rearranging the remaining terms, and reversing the inequality because a is negative, if:

$$P < -\frac{b}{a}.$$

In other words, the indirect method standard error is smaller than the direct method standard error if the State population is less than -b/a For 19861988, the smallest of the three values for -b/a, which is the same for all States, is over 180 million, which substantially exceeds the population of any State, thus proving the statement in the text about 93 percent to 94 percent of the direct method standard error in the median State. For 1988, the indirect method standard error fell short of the direct method standard error by more than ten percent for only four States. (For both 1986 and 1987, differences of such magnitude are obtained for six States.) The largest differences between the direct and indirect method standard error estimates pertain to States with the highest poverty rates.

Table V.7 displays alternative standard errors for direct sample estimates of State FSP eligibility counts. We use the direct and indirect methods described earlier to estimate standard errors. The indirect method standard errors in Table V.7 are also displayed in Table V.2.

The indirect method standard errors in Table V.7 are smaller than the direct method standard errors, as expected Across the 51 States, the indirect method standard errors range from about 83 percent of the direct method standard errors in 1987 and 1988 (81. percent in 19%) to about 97 percent of the direct method standard errors in 1987 and 1988 (98 percent in 1986). The indirect method standard error is about 92 percent to 93 percent of the direct method standard error in the median State.

As noted earlier, Tables V.l, V.2, and V.3 display standard errors obtained using the indirect method_ Although indirect method standard errors may slightly overstate the precision of our estimates of poverty, FSP eligibility, and FSP participation, such standard errors facilitate comparisons among the direct sample estimates, the regression estimates, and the shrinkage estimates, and comparing estimates is the principal objective of this study. For reasons given in Chapter IV, we specify our regression and shrinkage models in terms of poverty rates or FSP eligibility rates. Therefore, we must use the indirect method to calculate standard errors for the poverty counts and FSP eligibility counts implied by our regression and shrinkage estimates of poverty rates and FSP eligibility rates. To obtain comparable standard errors for our direct sample estimates, we use the indirect method. Our conclusions about the relative precision of direct sample estimates are not influenced by our choice of the indirect method because the standard errors of the regression and shrinkage estimates are substantially smaller than the standard errors of the direct sample estimates using either method

B. REGRESSION RESULTS

This section describes our empirical results **obtained with** the regression method. In Chapter IV, we outlined our model fitting strategy, a strategy for selecting the "best" regression model. Section 1 descrii the results from our application of that strategy. Section 2 presents our regression estimates for poverty, **FSP eligibility,** and FSP participation.

1. Selecting the Best Regression Models

As noted in Chapter IV, our criterion variables in the regression models are direct sample estimates of poverty rates or FSP eligiiility rates. Our symptomatic indicators are:

- AFDC-the proportion of individuals in the State receiving Aid to Families with Dependent Children
- SSI-the proportion of individuals in the State receiving Supplemental Security Income
- INCOME--State per capita total personal income (in millions of dollars per person)
- CRIME--the State crime rate (the number of violent and property crimes per 100,000 population)
- LOWBIRTH-low birthweight births (less than 2,500 grams) as a proportion of all live births in the State
- OILGAS--a dummy variable equal to one if one percent or more of the State's total personal income is attributable to the oil and gas extraction industry
- UNEWENG-a dummy variable equal to one if the State is an upper New England State (the New England census division minus Connecticut)

These symptomatic indicators are described in greater detail in Appendix B.

We are reluctant to include dummy variables for geographic areas, such as UNEWENG, in our regression models because such variables leave unexplairied the underlying socioeconomic conditions associated with the differential incidence of poverty or FSP eligibility. Nevertheless, our preliminary analyses uncovered a strong, persistent upper New England effect. We discovered no other such effects using dummy variables for other geographic areas.

Our model fitting procedure selects the best one-variable model, the best two-variable model, the best three-variable model, and so forth. The best three-variable model, for example, is the three-symptomatic-indicator model with the highest R^2 and with t-statistics greater than two fix all three symptomatic indicators.[9] From among the best models, we select the three-variable model, for example, as the best overall if the models with four or more variables do not account for a substantially greater proportion of the interstate variability in poverty or FSP eligibility. Reviewing the results from previous studies using the regression method, Ericksen and Kadane (1985) noted that the most accurate estimates are generally-obtained using from- two to five -symptomatic indicators.

Our model fitting procedure produces consistent results across the six combinations defined by the two criterion variables (poverty rate and FSP eligibility rate) and three years (1986, 1987, and 1988). For five combinations, SSI is the symptomatic indicator in the best one-variable model. The exception, the best poverty rate model for 1986, has INCOME rather than SSI as the symptomatic indicator. R^2 is usually about 0.53 for the best one-variable models. The best two-variable models, with R^2 equal to about 0.74, explain just over 20 percent more of the variation in the criterion variables than the best one-variable models. For all six combinations, SSI and INCOME are the symptomatic indicators in the best two-variable models. SSI, INCOME, and UNEWENG are the symptomatic indicators in the best three-variable models for four of the six combinations. SSI, INCOME, and OILGAS are the symptomatic indicators in the best three-variable poverty and FSP eligibility rate models for 1988. R^2 is usually somewhat over 0.81 for each of the best three-variable models. Although SSI, INCOME, OILGAS, and CRIME are the symptomatic indicators in the best four-variable poverty rate model for 1988, UNEWENG replaces CRIME in the best four-variable

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[9] Although we also require that the sign of each regression coefficient make sense, this requirement did not preclude our considering a model that satisfies the other requirements.

1986 and 1987 poverty rate models and 1986, 1987, and 1988 eligibility rate models. The typical R^2 in the best four-variable models is 0.84. The five-variable models with the highest R^2 values generally explain just under 85 percent of the variability in poverty rates or FSP eligibility rates. None of the six five-variable models with the highest values for R^2 has t-statistics greater than two for all five symptomatic indicators.[10,11]

Our objective is to identify six best regression models, a best model for each of the two criterion variables (poverty and FSP eligibility) in each of three years (1986, 1987, and 1988). The gain in explanatory power from adding a second variable to a one-variable model and from adding a third variable to a two-variable model is always substantial according to the R^2 values obtained. The gain from adding a fourth variable to a three-variable model, although much smaller, is always sufficiently large to justify selecting a four-variable model over a three-variable model.[12] However, as noted earlier, the gain from adding a fifth variable to a four-variable model is negligible.[13] Moreover, all of the five-variable models with the highest R^2 values have at least one symptomatic variable that is not significant. Thus, all six of our overall best regression models have four symptomatic indicators. SSI, INCOME, UNEWENG, and OILGAS are the symptomatic indicators in five of the six models.

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[10]SSI INCOME, UNEWENG, OILGAS, and AFDC are the symptomatic indicators in the poverty rate models for 1986 and 1987 with the highest R^2 values. LOWBIRTH replaces AFDC in the FSP eligibility rate models for 1986 and 1987 with the highest R^2 values. SSI, INCOME, UNEWENG, OILGAS, and CRIME are the symptomatic indicators in the poverty rate and FSP eligibility rate models for 1988 with the highest R^2 values.

[11]Of all the possible five-variable models, only one has t-statistics greater than two for all five symptomatic indicators_ That model, the 1986 poverty rate model with AFDC, LOWBIRTH, INCOME, OILGAS, and UNEWENG, has an R^2 equal to 0.77.

[12]There is a gain in explanatory power even according to measures that penalize the addition of variables. For all six combinations, both $\bar{R}^2$ and $\tilde{R}^2$, defined in Chapter IV, are greater for the best four-variable model than for the best three-variable model.

[13]For the 1986 and 1987 FSP eligibility rate models, both $\bar{R}^2$ and $\tilde{R}^2$ are slightly smaller for the five-variable models than for the four-variable models. For the 1986 and 1987 poverty rate models, $\tilde{R}^2$ is slightly smaller for the five-variable model, while $\bar{R}^2$ is slightly larger for the five-variable model. Both $\bar{R}^2$ and $\tilde{R}^2$ are slightly larger for the five-variable poverty rate and FSP eligibility rate models for 1988.

The best 1988 poverty rate model includes CRIME rather than UNEWENG.[14] Estimated coefficients for these overall best regression models are presented in Appendix C.

2 Regression Estimates

The following subsections present our regression estimates of State poverty rates, State FSP eligibility rates, State poverty counts, State FSP eligibility counts, and State FSP participation rates. Subsection f assesses the sensitivity of our regression estimates to model specification.

a. Regression Estimates of State Poverty Rates

Table V.8 displays regression estimates of State poverty rates for 1986, 1987, and 1988. Table V.8 also gives standard errors for the estimated rates.

According to Table V.8, the median poverty rates in 1986, 1987, and 1988 were 13.0 percent, 12.5 percent, and 11.8 percent, respectively. The median rate for 1988 was 124 percent according to the direct sample estimation method. For 1986 and 1987, the methods yield median estimates that agree closely. The national poverty rates implied by our regression estimates for States were 13.8 percent, 13.6 percent, and 13.0 percent. The national poverty rates implied by our direct sample estimates were very similar at 13.6 percent, 13.5 percent, and 13.0 percent. Although the distributions of poverty rates implied by the regression and direct sample estimation methods are similar, fewer States had poverty rates under 10 percent in 1987 and 1988 according to the regression method, and more had poverty rates between 10 and 15 percent. Regression estimates imply the same geographic pattern as direct sample estimates. Poverty rates tended to be relatively low among States in the New England census division and relatively high among States in the East South Central and West South Central census divisions.

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[14]We suspect that the variable AFDC does not enter any of the beat regression models because the pattern of substantial variations among States in AFDC Program eligibility standards and benefits weakens the association between the incidence of AFDC receipt and the incidence of poverty or FSP eligibility. In particular, several very high poverty rate States have relatively low AFDC benefits.

According to Table V.8 (and Table V.4), the standard errors for our regression estimates are substantially smaller than the standard errors for the direct sample estimates. For 1988, the regression standard errors are less than one percent for 49 States, while the direct sample standard errors are less than one percent for just 9 States. For each year, the median standard error of regression estimates is 0.5 percent, 1.2 Percentage points below the median standard error of direct sample estimates. The 95 Percent confidence interval for the median State is nearly 5 percentage points narrower--2.0 percentage points wide compared with 6.7 percentage points wide-using the regression estimator instead of the direct sample estimator. The widest 95 percent confidence interval for a 1988 regression estimate is 3.9 percentage points wide (for Mississippi and the District of Columbia). Only ten States have 95 percent confidence intervals that are this narrow or narrower for 1988 direct sample estimates.

b. Regression Estimates of State FSP Eligibility Rates

Table V.9 displays regression estimates of State FSP eligibility rates for 1986, 1987, and 1988. Table V.9 also gives standard errors for the estimated rates.

According to Table V.9, the median FSP eligibility rates in 1986, 1987, and 1988 were 15.7 percent, 14.9 percent, and 13.9 percent, respectively. These values are 0.1, 0.1, and 0.4 percentage points lower than the direct sample estimates. For all three years, the regression and direct sample estimates imply similar distributions of eligibility rates across broad rate categories (less than 10 percent, 10 percent to 15 percent, and so forth) and across census divisions.

According to Table V.9 (and Table V.5), the standard errors for our regression estimates of State FSP eligibility rates are substantially smaller than the standard errors for our direct sample estimates. For 1988, the regression standard errors are less than one percent for 42 States, while the direct sample standard errors are less than one percent for just 3 States. For each year, the median standard error of regression estimates is 0.6 percent, 1.3 percentage points below the median standard error of direct sample estimates. The 95 percent confidence interval for the median State is 5 percentage points narrower--24 percentage points wide compared with 7.4 percentage points wide--using the regression estimator instead of the direct sample estimator.

c. Regression Estimates of State Poverty Counts

Table V.10 displays regression estimates of State poverty counts for 1986, 1987, and 1988. Table V.10 also gives standard errors for the estimated counts. We derive the standard errors by multiplying the standard errors of estimated poverty rates by State population totals.

The regression estimates of State poverty counts imply that 31,751,000 individuals were in poverty in 1988 in the entire United States--6,000 more impoverished individuals than implied by the direct sample estimates. Regression estimates of State poverty counts range from 47,090 individuals in Alaska to 4,111,000 individuals in California. This range is about 12 percent wider than the range of direct sample estimates. ---The differences between United States totals from the regression and direct sample estimation methods are larger for 1986 and 1987 than for 1988 for which the difference is less than 0.1 percent. The regression method gives a 1.4 percent higher figure for 1986 and a 0.3 percent higher figure for 1987.

The standard errors of our regression estimates of poverty counts are substantially smaller than the standard errors of our direct sample estimates, With the direct sample estimation method, the standard error is more than 10 percent of the estimated 1988 poverty count for 39 States. With the regression method, the standard error is more than 10 percent of the estimated 1988 count for just three States. For the median State, the standard error of the regression estimate is 4.1 percent of the estimated 1988 count, while the standard error of the direct sample estimate is 14.2 percent of the estimated count. Using the regression method instead of the direct sample estimation method, we are able to narrow the widest 95 percent confidence interval--for California-from over 1,000,000 persons to about 655,000 persons. Based on our regression estimates, we are 95 percent confident that California bad between 3,784,000 and 4,439,000 poor people in 1988.

d. Regression Estimates of State FSP Eligibility Counts

Table V. 11 displays regression estimates of State FSP eligiiility counts for 1986, 1987, and 1988. Table V.ll also gives standard errors for the estimated counts, which we obtain by multiplying the standard errors of estimated eligiiility rates by State population totals.

According to Table V.11, 37,692,000 individuals were ehgiile for the FSP in 1988 for the entire United States-359,000 (one Percent) **more eligible** individuals than implied by the direct sample estimates. For 1986 and 1987, the regression estimates show 29 percent and 1.4 percent more eligible individuals in the United States than do the direct sample estimates. Regression estimates of State-FSP eligibility counts for 1988 range from 58,000 individuals in New Hampshire to 4,841,000 individuals in California. This range is about 18 percent wider than the range of direct sample estimates.

As with poverty counts, the standard errors of our regression estimates of FSP eligibility counts are substantially smaller than the standard errors of our direct sample estimates. With the direct sample estimation method, the standard error is more than 10 percent of the estimated 1988 eligiiility count for 35 States. With the regression method, the standard error is more than 10 percent of the estimated 1988 count for just three States. For the median State, the standard error of the regression estimate is 3.9 percent of the estimated 1988 count.

e. Regression Estimates of State FSP Participation Rates

Table V.12 displays regression estimates of State FSP participation rates for 1986, 1987, and 1988. Table V.12 also gives standard errors for the estimated participation rates. Participation counts are adjusted for errors in issuance. Our method for estimating participation rate standard errors is described in Chapter IV.

According to Table V.12, the median FSP participation rate was 433 percent in 1986, 44.4 percent in 1987, and 45.5 percent in 1988. These regression estimates are 0.6 and 1.1 percentage points lower than the direct sample estimates for 1986 and 1988 and 0.5 percentage points higher than the direct sample estimate for 1987. The national participation rates implied by our regression estimates for States were 45.8 percent, 46.4 percent, and 47.5 percent in 1986, 1987, and 1988, respectively. These estimates are 13, 0.6, and 0.5 percentage points lower than the national participation rates calculated from our direct sample estimates for States. The regression and direct sample estimation methods imply similar distributions of participation rates across broad categories of rates. Table V.12 shows that participation rates tended to be relatively high among States in the Middle Atlantic census division and among some States in the East North Central census division and relatively low among States in the South Atlantic and Mountain census divisions. Participation rates were somewhat higher among States in the South Atlantic census division according to the direct sample estimates.

The standard errors of our regression estimates of State FSP participation rates are substantially smaller than the standard errors of our direct sample estimates. FOF 1988, the smallest direct sample standard error is 2.0 percent There are 28 States with regression standard errors under 20 percent The median standard error of our regression estimates is 1.5 percent for 1986, 1.6 percent for 1987, and 1.8 percent for 1988, or about 3.5 to 4.0 percentage points lower than the median standard error of our direct sample estimates. For 1986, the 95 percent confidence interval for the median State is only 6 percentage points wide compared with 20 percentage points wide with the direct sample estimator.

f. The Sensitivity of Regression Estimates to Model Specification

Our empirical results show that the standard errors of our regression estimates are substantially smaller than the standard errors of our direct sample estimates. Despite this apparent dominance of the regression method, a potentially serious limitation is that similar regression models could produce very different results.

The model fitting procedure used in this study identified a best overall regression model for each year and each criterion variable. The procedure also rejected models that were nearly as good as the best model. Although the model fitting procedure performed well in this study and for Ericksen and Kadane (1987), another fitting procedure that is equally reasonable might select one of these rejected models as the best. Thus, it is desirable that the best model identified by our procedure and a "nearly-the-best" model yield similar results. A complete sensitivity analysis is beyond the scope of this study. However, we compare the estimates obtained from the best poverty rate model for 1988 with the estimates obtained from a close competitor.

The best poverty rate model for 1988 has SSI, INCOME, OILGAS, and CRIME as symptomatic indicators. R^2 is slightly over 0.85. The next-best poverty rate model for 1988 has the same symptomatic indicators, except UNEWENG replaces CRIME. The t-statistics on all four symptomatic indicators exceed two, and R^2 is slightly under 0.85.[15]

Table V.13 displays regression estimates of State poverty rates for 1988 obtained from the best and next-best regression models. Table V.13 also gives standard errors for the estimated poverty rates.

According to Table V.13, the best regression model gives the higher poverty rate estimate for 19 States. The poverty rate estimates are equal for three States. The median percentage point difference (in absolute value) between estimates for the same State is 0.5. The percentage point difference is at least 1.0 (in absolute value) for 11 States. The median value for the difference between the two estimates expressed as a percentage of the estimate from the best model is 4.3 percent The difference between estimates is greater than ten percent of the estimate from the best model for eight States.

One way to judge the similarity of not only the point estimates but also their standard errors is to examine interval estimates. For each State, we can calculate the 95 percent confidence interval implied by each model and determine the extent to which the confidence intervals overlap. The more

[15]The model with SSI, INCOME, OILGAS, and LOWBIRTH also has an R^2 value slightly under 0.85 and just below the R^2 value for the model with UNEWENG. We consider the model with UNEWENG because it is the best poverty rate model for 1986 and 1987 and the best FSP eligibility rate model for all three years.

similar are the estimates and standard errors, the greater is the overlap for a State. To measure the extent of overlap, we can express the length of the segment that is common to the two confidence intervals as a percentage of the length of the longer of the two confidence intervals.

The estimates in Table V.13 imply that, in the median State, the overlapping segment of the two confidence intervals is 72 percent of the longer confidence interval. Thus, 28 percent of the longer confidence interval lies outside the other confidence interval in the typical State. The percentage overlap is less than 50 in 11 States and greater than 80 in just 16 States. For Rhode Island-the State with the smallest percentage overlap-we are 95 percent confident on the basis of the best regression model that the State's 1988 poverty rate was between 112 percent and 124 percent Using the next-best regression model, we are 95 percent confident that Rhode Island's 1988 poverty rate was between 86 percent and 11.8 percent For Rhode Island, the substantial nonoverlap is caused partly by one confidence interval being much longer than the other. For Virginia, the two regression models give 1988 poverty rate estimates of equal precision and confidence intervals of equal length. However, there is little-only about 50 percent--overlap between the confidence intervals. Using the best regression model, we are 95 percent confident that Virginia's 1988 poverty rate was between 9.2 percent and 10.8 percent. Using the next-best regression model, we are 95 percent confident that Virginia's 1988 poverty rate was between 10.0 percent and 11.6 percent. It seems that regression estimates may be fairly sensitive to model specification. Such sensitivity along with bias are serious limitations.

C SHRINKAGE ESTIMATES

The following sections present our shrinkage estimates of state poverty rate& state FSP eligibility rates, State poverty counts, State FSP eligibility counts, and State FSP participation rates. Section 6 assesses the sensitivity of shrinkage estimates to model specification and errors in standard error estimates.

1. **Shrinkage Estimates of State** Poverty Rates

Table V.14 displays shrinkage estimates of State poverty rates for 1986, 1987, and 1988. Table V.14 also gives standard errors for the estimated rates. We obtain these estimates and the other estimates reported in this section using the hierarchical Empirical Bayes estimator descrii in Chapter IV. With this estimator, we calculate a weighted average of the direct sample estimates from Section A and the regression estimates from Section B.

According to Table V.14, the median poverty rates in 1986, 1987, and 1988 were 128 percent, 128 percent, and 11.8 percent, respectively. The median rate for 1988 was 124 percent according to the direct sample estimation method. The shrinkage and direct sample estimation methods yield similar median estimates for 1986 and 1987, while the shrinkage and regression methods yield similar median estimates for all three years. The national poverty rates implied by our shrinkage estimates for States were 13.6 percent, 13.5 percent, and 13.0 percent. The distributions of poverty rates implied by the three estimation methods are similar, but more States with poverty rates under 15 percent had poverty rates under 10 percent in 1987 and 1988 according to the direct sample estimation method. All three estimators imply the same geographic pattern of poverty rates. Poverty rates tended to be relatively low among States in the New England census division and relatively high among States in the East South Central and West South Central census divisions.

According to Table V.14, the standard errors of our shrinkage estimates of State poverty rates are smaller than the standard errors of our direct sample estimates and larger than the standard errors of our regression estimates. For 1988, shrinkage standard errors are under one percent for 27 States, while the direct sample standard errors are under one percent for 9 States and the regression standard errors are under one percent for 49 States. Shrinkage and regression standard errors are under 1.5 percent for all 51 States, while direct sample standard errors are under 1.5 percent for only 12 States. The median shrinkage standard error for 1988 is 0.9 percent, 0.8 percentage points below the median direct sample standard error and 0.4 percentage points above the median regression standard error. The 95 percent confidence interval for the median State is 3.5 percentage points wide compared with 6.7 percentage points wide with the direct sample estimator and 20 percentage points wide with the regression estimator.

2 Shrinkage Estimates of State FSP Eligibility Rates

Table V.15 displays shrinkage estimates of State FSP eligibility rates for 1986, 1987, and 1988. Table V.15 also gives standard errors for the estimated rates.

According to Table V.15, the median FSP eligibility rates in 1986, 1987, and 1988 were 153 percent, 14.8 percent, and 13.7 percent, respectively. These values are 0.5, 0.2, and 0.6 percentage points lower than the direct sample estimates and 0.4, 0.1, and 0.2 percentage points lower than the regression estimates. For each year, the three methods yield similar distributions of eligibility rates across broad rate categories and across census divisions.

According to Table V.15, the standard errors of our shrinkage estimates of State FSP eligibility rates are smaller than the standard errors of our direct sample estimates and larger than the standard errors of our regression estimates. Although direct sample standard errors are under 1.5 percent for only 12 States, shrinkage standard errors are under 1.5 percent for 49 States, and regression standard errors are under 1.5 percent for all 51 States. For each year, the median shrinkage standard error is about 1.2 percent, 0.7 percentage points below the median direct sample standard error and 0.6 percentage points above the median regression standard error. The 95 percent confidence interval for the median State is 4.7 percentage points wide compared with 7.4 percentage points wide with the direct sample estimator and 24 percentage points wide with the regression estimator.

3. Shrinkage Estimates of State Poverty Counts

Table V.16 displays shrinkage estimates of State poverty counts for 1986, 1987, and 1988. Table V.16 also gives standard errors for the estimated counts. We obtain the standard errors by multiplying the standard errors of estimated poverty rates by State population totals.

The shrinkage estimates of State poverty counts imply that 31,566,000 individuals were in poverty in 1988 for the entire United States--179,000 (0.6 percent) fewer poor people than implied by the direct sample estimates and 185,000 fewer poor people than implied by the regression estimates. Shrinkage estimates of State poverty counts range from 49,000 individuals in Alaska to 3,841,000 individuals in California This range is about four percent wider than the range of direct sample estimates. The range of regression estimates is about 12 percent wider than the range of direct sample estimates. The differences between United States totals from the shrinkage and direct sample estimation methods are even smaller for 1986 and 1987. The shrinkage method yields a 0.1 percent lower figure for 1986 and a 0.3 percent lower figure for 1987. Compared with the United States total from the direct sample estimation method, the regression method yields a 1.4 percent higher figure for 1986 and a 0.3 percent higher figure for 1987. The 1988 difference is less than 0.1 percent.

The standard errors of our shrinkage estimates of poverty counts are substantially smaller than the standard errors of our direct sample estimates but somewhat larger than the standard errors of our regression estimates. With the direct sample method, the standard error is more than 10 percent of the estimated 1988 poverty count for 39 States. With the shrinkage method, the standard error is more than 10 percent of the estimated 1988 count for just six States. For the median State, the standard error of the shrinkage estimate is 8.0 percent of the estimated 1988 poverty count. The standard error of the regression estimate is that large relative to the estimated count for only four States. The standard error of the direct sample estimate is 13.6 percent of the estimated count for the median State.

4. Shrinkage Estimates of State FSP Eligibility Counts

Table V.17 displays shrinkage estimates of State FSP eligibility counts for 1986, 1987, and 1988. Table V.17 also gives standard errors for the estimated counts, which we obtain by multiplying the standard errors of estimated eligibility rates by State population totals.

According to Table V.17, 37,212,000 individuals were eligible for the FSP in 1988 in the entire United States-121,000 (0.3 percent) fewer eligible individuals than implied by the direct sample estimates and 480,00 fewer eligible individuals than implied by the regression estimates. For 1986 and 1987, the shrinkage estimates show less than 0.1 percent more eligible individuals in the United States than do the direct sample estimates. The regression estimates show W percent and 1.4 percent more eligible individuals in the United States than do the direct sample estimates for 1986 and 1987. Shrinkage estimates of State FSP eligibility counts for 1988 range from 64,000 individuals in Vermont to 4,290,000 individuals in California. This range is about four percent wider than the range of direct sample estimates. The range of regression estimates is about 18 percent wider than the range of direct sample estimates.

As with the poverty counts, the standard errors of our shrinkage estimates of FSP eligibility counts are substantially smaller than the standard errors of our direct sample estimates and somewhat larger than the standard errors of our regression estimates. With the direct sample estimation method, the standard error is more than 10 percent of the estimated 1988 count for 35 States. With the shrinkage method, the standard error is more than 10 percent of the estimated 1988 count for 11 States. For the median State, the standard error of the shrinkage estimate is 8.8 percent of the estimated 1988 count, while the standard error of the direct sample estimate is 12.9 percent of the estimated count. The standard error of the regression estimate is as large as 8.7 percent of the estimated count for only four States.

5. Shrinkage Estimates of state FSP Participation Rates

Table V.18 displays shrinkage estimates of State FSP participation rates for 1986, 1987, and 1988. Table V.18 also gives standard errors for the estimated participation rates. Participation counts are adjusted for errors in issuance. Our method for estimating participation rate standard errors was descrii in Chapter IV.

According to Table V.18, the median FSP participation rate was 44.0 percent in 1986, 433 percent in 1987, and 46.1 percent in 1988. These shrinkage estimates are 0.6 and 0.5 percentage points lower than the direct sample estimates for 1987 and 1988 and 0.1 percentage points higher than the direct sample estimate for 1986. The regression estimates are 0.6 percentage points lower, 0.5 percentage points higher, and 1.1 percentage points lower than the direct sample estimates for 1986, 1987, and 1988. The national participation rates implied by our shrinkage estimates for States were 47.1 percent, 47.0 percent, and 48.1 percent in 1986, 1987, and 1988, respectively. The 1986 and 1987 estimates equal to the nearest tenth of a percent the national participation rates calculated from our direct sample estimates for States, and the 1988 estimate is only 0.1 percentage points higher than the direct sample estimate. In contrast, the national participation rates calculated from our regression estimates for States are 1.3, 0.6, and 0.5 percentage points lower than the national participation rates calculated from our direct sample estimates for States. For 1986 and 1987, about one-third of the States had participation rates below 40 percent, about one-third of the States had participation rates of at least 40 percent but below 50 percent, and about one-third of the States had participation rates of 50 percent or more. The regression and direct sample methods imply similar distributions of participation rates. All three estimation methods show a movement of States out of the under-40 percent participation rate category over time, although the departure from the one-third/one-third/one-third distribution is greatest according to the shrinkage estimates. The three estimation methods imply similar geographic patterns.

The standard errors of our shrinkage estimates of State FSP participation rates are smaller than the standard errors of our direct sample estimates and larger than the standard errors of our regression estimates. For 1988, the shrinkage standard errors are less than three percent for 12 States, while the direct sample standard errors are less than three percent for 5 States and the regression standard errors are less than three percent for 42 States. Although 30 States have direct sample estimator standard errors of five percent or more for 1988 participation rate estimates, only

3 States have regression estimator standard errors that large and only 10 States have shrinkage estimator standard errors that large. The median standard error of our shrinkage estimates is 3.0 percent for 1986, 3.4 percent for 1987, and 3.9 percent for 1988, always about two percentage points lower than the median standard error of our direct sample estimates and about twice the median standard error of our regression estimates. For 1988, the 95 percent confidence interval for the median State is 15 percentage points wide compared with 22 percentage points wide with the direct sample estimator and 7 percentage points wide with the regression estimator.

6. The Sensitivity of Shrinkage Estimates to Model Specification and Errors in Standard Error Estimates

The results in Section B show that regression estimates can be sensitive to how the regression model is specified, that similar models can produce different results. Our shrinkage estimator combines direct sample estimates and regression estimates. Thus, a potential limitation of the shrinkage estimator is that the shrinkage estimates may be sensitive to how the regression model is specified. Similar shrinkage models based on similar regression models may produce different results. Our analysis of this issue will follow our analysis in Section B of the sensitivity of regression estimates.

Table V.19 displays shrinkage estimates of State poverty rates for 1988 obtained by combining direct sample estimates with regression estimates from the best or the next-best regression models. As noted in Section B, the best poverty rate regression model for 1988 has SSI, INCOME, OILGAS, and CRIME as symptomatic indicators. The next-be& model replaces CRIME with UNEWENG. Table V.19 also gives standard errors of the shrinkage estimates of poverty rates.

According to Table V.19, the median percentage point difference (in absolute value) between shrinkage estimates for the same State from the best and next-best shrinkage models is 0.3, just over half the median percentage point difference of 0.5 between regression estimates from the best and next-best regression models. The percentage point difference between shrinkage estimates is at least 0.5 (in absolute value) for 19 States and at least 1.0 (in absolute value) for 3 States-7 fewer States and 8 fewer States than for regression estimates. When the difference between the two shrinkage estimates for a State is expressed as a percentage of the estimate from the best model, the median value obtained is 2.6 percent, down from 43 percent for the regression estimates. The difference between shrinkage estimates is greater than ten percent of the estimate from the best model for two States. The difference between regression estimates is that large for eight States.

As in Section B, we can assess the similarity of the two sets of shrinkage estimates and their standard errors by measuring the overlap of the implied confidence intervals for the State. To measure overlap, we express the length of the segment that is common to the two 95 percent confidence intervals as a percentage of the length of the longer of the two confidence intervals.

The results displayed in Table V.19 imply that, for the median State, the overlapping segment of the two confidence intervals is 87 percent of the longer confidence interval. Thus, just 13 percent of the longer confidence interval lies outside the shorter confidence interval in the typical State. Thii nonoverlap for shrinkage estimator confidence intervals is less than half of the nonoverlap for regression estimator confidence intervals. For confidence intervals from the best and next-best shrinkage models, the percentage overlap is greater than 50 for all 51 States and greater than 80 for 42 States. The overlap in confidence intervals from the best and next-best regression models is less than 50 percent for 11 States and greater than 80 percent for only 16 States. Thus, the shrinkage method dampens differences between competing models.

Another potential limitation of our shrinkage estimator pertains to the estimated standard errors of the direct sample estimates. As noted by Ericksen and Kadane (1987), the Empirical Bayes shrinkage estimator assumes that the standard errors of the direct sample estimates are known with certainty and are not estimated. For this study, we must rely on estimated standard errors, which are subject to sampling variability and nonsampling error. It is possible that we would obtain different shrinkage estimates if our estimated standard errors for direct sample estimates were different. Our shrinkage estimator results may be sensitive to variations in the estimated standard errors for direct sample estimates.

Although a complete sensitivity analysis is beyond the scope of this study, we assess the potential effects of substantially understating the standard errors of our direct sample estimates of FSP eligibility rates. We noted earlier in this chapter that, because we must simulate FSP eligibility status for individuals in the CPS, we must interpret the estimated standard errors of our direct sample estimates of FSP eligibility rates with caution. It is possible that our estimated standard errors overstate the precision of our FSP eligibility estimates. Such errors may influence our shrinkage estimates.

To analyze the sensitivity of our shrinkage estimates of FSP eligibility rates, we compare the shrinkage estimates obtained using the estimated standard errors from the direct sample estimation method with the shrinkage estimates obtained using the estimated standard errors inflated by 20 percent for each State. A 20 percent downward bias in estimated standard errors seems fairly large.

Table V.20 displays shrinkage estimates of State FSP eligibility rates for 1988 obtained using either the estimated standard errors from the direct sample estimation method or the estimated standard errors inflated by 20 percent for each State. Table V.20 also gives standard errors for the shrinkage estimates.

Shrinkage estimates are weighted averages of direct sample estimates and regression estimates. An expected effect of inflating the standard errors of direct sample estimates is that the shrinkage estimator weights the direct sample estimates less heavily and the regression estimates more heavily. Our empirical results show that inflating the standard errors of the direct sample estimates pulls the shrinkage estimates back away from the direct sample estimates toward the regression estimates. For the 1988 FSP eligibility rate estimates, the shrinkage estimate is about half of the distance from the regression estimate to the direct sample estimate in the median State when the estimated standard errors are used. When the inflated standard errors are used, the shrinkage estimate is just over one-third of the distance from the regression estimate to the direct sample estimate.

According to Table V.20, inflating the standard errors of direct sample estimates does not cause large changes in the shrinkage estimates of FSP eligibility rates. For the median State, the difference (in absolute value) between the alternative shrinkage estimates is 0.2 percentage points. Shrinkage estimates differ by 0.5 percentage points or more (in absolute value) for only eight States. If we express the difference between shrinkage estimates as a percentage of the estimate obtained when the estimated standard errors are used, the median value calculated is 1.7 percent. The percentage difference exceeds five percent for only four States.

As in our previous sensitivity analyses, we can examine the overlap in 95 percent confidence intervals to assess the similarity of both the point estimates of eligibility rates and their standard errors. We again measure overlap by expressing the length of the segment that is common to a State's two confidence intervals as a percentage of the length of the longer confidence interval.

The results displayed in Table V.20 imply that, for the median State, the overlapping segment of the two confidence intervals is more than 91 percent of the longer confidence interval, Thus, less than nine percent of the longer confidence interval lies outside the shorter confidence interval in the typical State. The percentage overlap exceeds 83 percent for 50 of the 51 States and 90 percent for 32 States. We conclude that our shrinkage estimates are not sensitive to even large errors in estimated standard errors for direct sample estimates. This result is consistent with Ericksen and Kadane's (1987) findings.[16]

D. AN ASSESSMENT OF ALTERNATIVE ESTIMATES

In the previous sections of this chapter, we have noted some of the similarities and differences among estimates from the three estimation methods. In this section, we examine the similarities and

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[16]We examined one other issue pertaining to model specification and found that whether the District of Columbia is included or excluded has very little effect on either the regression or the shrinkage estimates for the other 50 States.

differences more closely and assess their implications. We focus on estimates for one year, 1988, to facilitate our assessment

Our assessment examines the similarities and differences in the distriiutions of States estimates, in the point estimates for individual States, in the precision of estimates, and in the interval estimates (confidence intervals) for individual States. We also assess the relative sensitivity of alternative estimates to, for example, model specification.

We find that the three estimation methods generally agree on aggregate characteristics pertaining to the distributions of State estimates, characteristics such as the median State poverty rate and the distribution of State FSP participation rates across broad rate categories. Despite this agreement on aggregate characteristics, we find that, for some individual States, the three alternative point estimates for a given year differ substantially. However, many of the dierences can be attributed largely to sampling variability. When we compare interval estimates, that is, confidence intervals, we find that the regression and shrinkage methods mainly reduce our uncertainty, providing narrower confidence intervals than the direct sample method. For most States, the regression and shrinkage confidence intervals lie entirely inside the direct sample confidence intervals. Nevertheless, there is evidence of substantially greater bias in regression estimates than in shrinkage estimates. Furthermore, examining the precision of alternative estimates, we find that our estimated standard errors exaggerate the overall precision of the regression estimates. We find that the covariances between regression estimates for different States are relatively large. Thus, the risk of obtaining many large estimation errors is higher with the regression method than with the direct sample and shrinkage methods.

Tables V.21 to V.25 display estimates of, respectively, State poverty rates, State FSP eligibility rates, State poverty counts, State FSP eligibility counts, and State FSP participation rates for 1988. Each table displays direct sample estimates, regression estimates, and shrinkage estimates and standard errors for all estimates. Ail of the estimates in Tables V.21 to V.25 are displayed in the tables discussed previously in this chapter. For example, Table V.21 collects estimates for 1988 from Tables V.4, V.8, and V.14.

1. Similarities in the Alternative Distributions of State Estimates

On a national estimate, on an estimate for the average State, and on the distribution of States among broad categories, there is general agreement among the direct sample, regression, and shrinkage estimators. According to Table V.21, the three national poverty rate estimates for 1988 agree to the nearest tenth of a percent. According to Table V.25, the highest and lowest of the three national FSP participation rate estimates for 1988 differ by just 0.6 percentage points. Differences for estimates of poverty and FSP participation rates pertaining to the median State are similar.[17]

An important result is that, while there is generally close agreement among alternative estimates of national counts and rates, the differences between direct sample and shrinkage estimates tend to be smaller than differences between direct sample and regression estimates. Shrinkage estimates are closer to the direct sample estimates for two of the three years' national poverty counts and for all three years' national FSP eligibility counts. Because the direct sample estimates of national totals are fairly precise, especially compared to the State estimates, this finding offers some confirmation that the shrinkage estimates are subject to less bias than the regression estimates.

As noted in earlier sections of this chapter, the three estimation methods imply similar distributions of States across broadly defined categories for both participation and poverty. For example, about one-third of the States had FSP participation rates below 40 percent, about one-third of the States had FSP participation rates between 40 and 50 percent, and about one-third of the States had FSP participation rates of 50 percent or more in each of the three years according to all three methods. There is also little disagreement among the three methods on the number of States that had 1988 poverty rates under 15 percent, although more States had 1988 poverty rates under 10 percent according to the direct sample estimation method than according to the other two methods.

[17]Differences tend to be slightly larger for 1986 and 1987.

Two common problems, noted by Ericksen and Kadane (1987), are that direct sample estimates may overstate differences among States and regression estimates may understate differences among States. Common measures of variability-the standard deviation, the range, and the interquartile range-suggest that the direct sample estimates do exaggerate interstate variations in poverty rates and FSP participation rates. The same measures, however, do not provide convincing evidence that the regression method oversmooths direct sample estimates.[18] The standard deviation of the 51 State poverty rate estimates for 1988 is 4.6 percent for the direct sample estimation method, 42 percent for the regression method, and 4.1 percent for the shrinkage method. Although the range of the direct sample estimates of 1988 poverty rates is 12 percent greater than the range of the regression estimates and 14 percent greater than the range of the shrinkage estimates, the interquartile range of the direct sample estimates is 8 percent less than the interquartile range of the regression estimates.[19] The interquartile range of the direct sample estimates is 23 percent greater than the interquartile range of the shrinkage estimate!& For 1988 FSP participation rates, the standard deviation is 11.4 percent for the direct samples estimates, 103 percent for the regression estimates, and 10.1 percent for the shrinkage estimates. The range of the direct sample estimates exceeds the range of the regression estimates by 46 percent and the range of the shrinkage estimates by 14 percent. The interquartile range of the direct sample estimates exceeds the interquartile range of the regression estimates by 18 percent and the interquartile range of the shrinkage estimates by 7 percent.[20] Regression estimates may understate the variation in 1988 FSP participation rates

[18] This does not imply that the regression method does not understate differences between some individual pairs of States.

[19] If States are ranked 1 to 51 in descending order of their poverty rates, the range is the difference between the poverty rates of the 1st and 51st States, and the interquartile range is the difference between the poverty rates of the 13th and 39th States. Thus, the interquartile range is not affected by one or two extreme estimates. The interquartile ranges for the direct sample, regression, and shrinkage estimates are 4.8, 5.2, and 3.9 percentage points. respectively.

[20] The interquartile ranges are 173, 14.7, and 161 percentage points for the direct sample, regression, and shrinkage estimates, respectively.

among States, although the standard deviations of the regression and shrinkage estimates are roughly equal.[21]

2. **Differences in the Alternative Point Estimates for Individual States**

In the aggregate, estimates from the three methods are similar, Only when we examine estimates for individual States are large differences apparent. The median difference (in absolute value) between 1988 State poverty rate estimates from the direct sample estimation method and the regression method is 1.1 percentage points. The median difference between the direct sample and shrinkage estimates is 0.9 percentage points.[22] For 1988, the difference between the direct sample and regression estimates of poverty rates is greater than two percentage points for 14 States. For only seven States is the difference between the direct sample and shrinkage estimates that large. For 1988 State FSP participation rate estimates, the median difference between the direct sample and shrinkage estimates is 2.2 percentage points. The median difference between the direct sample and regression estimates is **4.2** percentage points, and the difference is over 10 percentage points for six States.[23]

The differences among estimates can sometimes cause, for example, one State to have a higher poverty rate than another State according to one estimator but a lower poverty rate according to an alternative estimator. Although the rank correlation between the direct sample and shrinkage estimates of 1988 poverty rates is 0.92, the rank correlation between the direct sample and regression estimates is 0.82 The rank correlation between the direct sample and shrinkage estimates of 1988

[21]We find no evidence of widespread oversmoothing for 1986 and 1987.

[22]For 1986 and 1987, the median differences between direct sample and regression estimates are 13 and 1.0 percentage points, while the median differences between direct sample and shrinkage estimates are 0.9 and 0.6 percentage points.

“For 1986 and 1987, the median differences between direct sample and regression estimates are 3.4 and 4.2 percentage points, while the median differences between direct sample and shrinkage estimates are 1.7 and 2.2 percentage points.

FSP participation rates is 0.91. The rank correlation between the direct sample and regression estimates, however, is 0.77."

Using direct sample estimates as a standard of comparison, we risk observing large differences between the direct sample estimates and the regression or shrinkage estimates because of large sampling errors in the direct sample estimates. To reduce this risk, we can compare estimates for States with the most precise direct sample estimates.

For the nine States with a direct sample estimate standard error under one percent, the median difference (in absolute value) between the direct sample and regression estimates of 1988 poverty rates is 1.4 percentage points, which is greater than the median difference of 1.1 percentage points for all 51 States. The median difference between the direct sample and shrinkage estimates for the nine States is 0.3 percentage points. The largest difference between the direct sample and shrinkage estimates for the nine States is 1.2 percentage points, and the next largest difference is 0.7 percentage points. The shrinkage estimate is closer than the regression estimate to the-direct sample estimate of the 1988 poverty rate for all nine States, and the difference between the shrinkage and direct sample estimates is just one-third of the difference between the regression and direct sample estimates, on average.

For the nine States with a standard error under four percent for the direct sample estimate of the 1988 FSP participation rate, the median difference between the direct sample and regression estimates of the participation rate is 3.4 percentage points. The median difference between the direct sample and shrinkage estimates is 1.4 percentage points for these States. The shrinkage estimate is closer than the regression estimate to the direct sample eatimate of the 1988 participation rate for seven of the nine States and equally close for one other State. Averaged across all nine States, the

[24]The rank correlation between the regression and shrinkage estimates is 0.97 for poverty rates and 0.95 for participation rates. The rank correlation is the correlation between the ranks-rather than the values--of the estimates. Each estimate is ranked from 1 to 51.

difference between the shrinkage and direct sample estimates is just over one-half the difference between the regression and direct sample estimates.

Similar patterns are observed when we compare alternative estimates for the 11 States with the largest CPS samples. For all three years, the median difference between shrinkage and direct sample poverty rate estimates is between one-quarter and one-third the median difference between regression and direct sample estimates. Approximately the same result pertains to FSP eligibility and participation rates. For eligibility rates, the largest difference in each year between the shrinkage and direct sample estimates for any of the 11 States is smaller than the median difference between regression and direct sample estimates.[25]

An important advantage of the shrinkage estimator relative to the regression estimator is that differences between direct sample and shrinkage estimates are substantially smalier than differences between direct sample and regression estimates for the States with the most precise direct sample estimates. With the similar result for differences among national estimates, this finding provides highly suggestive evidence that, as expected, shrinkage estimates are less biased, possibly much less biased, than regression estimates.

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[25]In combining direct sample and regression estimates, our shrinkage estimator gives greater weight to more precise direct sample estimates by design, all else equal. This is an important property, although it does not imply that for a State with a precise direct sample estimate, the shrinkage estimate will necessarily be much closer to the direct sample estimate than is the regression estimate. Both the regression and shrinkage estimates could be close to the direct sample estimate. In this application, that is generally not the case. We find that for the States with relatively precise direct sample estimates, the regression estimates often differ fairly substantially from the direct sample estimates, while the shrinkage and direct sample estimates usually agree closely. We focus our attention on the large States because in the absence of knowing the true values, the direct sample estimates for those States provide a more reliable standard of comparison for evaluating the regression and shrinkage estimates. Given the way the shrinkage estimator weights the direct sample and regression estimates in forming a compromise estimate, the relative agreement between the direct sample and shrinkage estimates is generally somewhat less for small States than for large States, which is desirable given the lack of precision of direct sample estimates for small States

3. Differences in the Precision of the Alternative Estimates

Thus far in this section, our comparisons of the empirical performance of estimators has focused on the values of point estimates and has largely ignored the precision of those estimates. As we noted in Chapter IV, we cannot estimate MSE matrixes for the regression and shrinkage estimators. Our comparisons, therefore, are limited to estimated standard errors, which do not take into account the biases in regression and shrinkage estimates.

According to Table V.21, the standard error of the direct sample estimate for the 1988 poverty rate is newer smaller than the standard error of the regression or shrinkage estimate. The median difference between the standard errors of the direct sample and regression estimates is 1.2 percentage points. The standard error of the direct sample estimate exceeds the standard error of the regression estimate by at least 1.5 percentage points for ten States. The median difference between the standard errors of the direct sample and shrinkage estimates is 0.8 percentage points. The standard error of the direct sample estimate exceeds the standard error of the shrinkage estimate by at least one percentage point for 11 States. Although the standard error of the shrinkage estimate is smaller than the standard error of the regression estimate for only two States (Florida and New Jersey), the differences between the standard errors of estimates from the two methods tend to be small. The median difference is 0.4 percentage points, and the maximum difference is just 0.6 percentage points.

According to Table V.25, patterns of differences among the standard errors for altemative estimates of 1988 FSP participation rates are similar to the patterns of differences among poverty rate standard errors, although the standard errors and differences for participation rates are much larger. The standard error of the direct sample estimate is at least 3.5 percentage points larger than the standard error of the regression estimate for half of the States and at least 5 percentage points larger than the standard error of the regression estimate for 15 States. The standard error of the direct sample estimate is at least 1.7 percentage points larger than the standard error of the shrinkage estimate for half of the States and at least. 5 percentage points larger than the standard error of the shrinkage estimate for 5 States.[26] The largest difference between the standard errors of shrinkage and regression estimates is four percentage points. The median difference is 1.8 percentage points.

Our results show that, for nearly all States, the direct sample estimate has the largest standard error and the regression estimate has the smallest standard error and that the standard error of the shrinkage estimate falls somewhere in between, typically closer to the standard error of the regression estimate. We reach this conclusion by examining differences between standard errors for one State after another. We have not yet considered the correlations between potential errors in State estimates. Such correlations are reflected in the off-diagonal elements of the variancecovariance matrix for an estimator.[27,28] Although we cannot determine for our estimators whether one MSE

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[26]The standard error of the direct sample estimate is smaller than the standard error of the regression estimate for only two States (New Hampshire and Massachusetts) and smaller than the standard error of the shrinkage estimate for just one State (New Hampshire).

[27]The diagonal elements of a variance-covariance matrix are the variances of the estimates, that is, the standard errors squared. The off-diagonal elements are the covariances between estimates. The covariance between two estimates is the correlation between those estimates times the product of the estimates' standard errors. Roughly, the covariance captures any tendency for the estimation errors to be related. A positive covariance between estimators for two States means that, when an unusually high estimate is obtained for one State, an unusually high estimate is typically obtained for the other State and, when an unusually low estimate is obtained for one State, an unusually low estimate is typically obtained for the other State.

[28]One use of the covariances between estimates is for testing whether States are significantly different. The standard error of the difference between Maryland's and Virginia's poverty rates, for example, is:

$$\sqrt{\mathrm{var}(p_{MD}) + \mathrm{var}(p_{VA}) - 2\mathrm{cov}(p_{MD}, p_{VA})},$$

where p_{MD} and p_{VA} are the poverty rates, $\mathrm{var}(p_{MD})$ and $\mathrm{var}(p_{VA})$ are the variances, and $\mathrm{cov}(p_{MD}, p_{VA})$ is the covariance. If the difference between Maryland's and Virginia's poverty rates divided by the standard error of the difference is greater than 1.96 or less than -1.96, we infer that the poverty rates are significantly different at the 95 percent level of confidence More precisely, we reject the hypothesis that the poverty rates are equal.

For direct sample estimates, all covariances are zero because independent samples are drawn in each State in the CPS. For both regression and shrinkage estimates, however, covariances between (continued...)

matrix is bigger than another MSE matrix, we can compare the sizes of the variance-covariance matrixes and determine whether one estimator is more "efficient" than another estimator.[29]

Comparing estimated variance-covariance matrixes pertaining to our 1988 poverty rate estimates, we find that the shrinkage estimator is more efficient than the direct sample estimator. Our findings from other comparisons, however, are inconclusive It is not possible to say that the regression estimator is more efficient than the direct sample estimator or that the regression estimator is more efficient than the shrinkage estimator.[30] The explanation for this last, seemingly anomalous result that the regression estimator is not the most efficient of the three estimators is that, although the standard errors of regression estimates tend to be relatively small, the covariances for many pairs of

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[28](...continued)
estimates for different States are generally nonzero for reasons given earlier. We do not present covariances in this report because, for each set of poverty, eligibility, or participation estimates, there are 1,275 covariances, one covariance for each possible pairing of States. However, we can reeommend a simple rule of thumb to use for calculating a standard error of a difference: assume that the covariance equals zero. This assumption will rarely influence the outcome of a hypothesis test

If we want to determine, for every pair of States, whether the States' 1988 poverty rates are significantly different, we must conduct 1,275 hypothesis tests. Using our shrinkage estimates, we will make the same inference whether we use the estimated covariance or assume the covariance is zero for all but nine (0.7 percent) of our significance tests. Moreover, each of our nine "errors" will be conservative in the following sense. Although the test using the estimated covariance suggests that the States' poverty rates are significantly different, we would not reject the hypothesis that they are equal using our rule of thumb that the covariance is zero. We are conservative in overstating the standard error of the difference, rather than exaggerating its precision. Based on our regression estimates for 1988 poverty rates, whether we use the estimated covariance or a zero covariance affects our inference for 88 (6.9 percent) of our significance tests. In just seven instances would we infer a significant difference when none exists. The other 81 "errors" would be conservative.

One manifestation of the greater precision of shrinkage estimates relative to direct sample estimates is that we arc better able to detect substantively important differences between States. According to the direct sample estimates of 1988 poverty rates, about two-thirds of the differences of 2.5 percentage points or more are statistically significant. According to the shrinkage estimates, nearly 94 percent of the differences of such magnitude are statistically significant. (Because direct sample estimates tend to overstate differences among States, there are more large differences according to those estimates.)

[29]Schmidt (1976) defines "efficiency.

[30]We obtain the same results on relative efficiency for 1986 and 1987 poverty rate estimators and for 1986, 1987, and 1988 FSP eligiibility rate estimators.

regression estimates are relatively large. A big error for one State will likely be accompanied by big errors for other States. Thus, there is a greater risk of obtaining large estimation errors for many States.

Tables V.21 to V.25 show that the standard errors of regression estimates are almost uniformly low, even for States with very large standard errors of direct sample estimates. Also, despite typically small differences between the regression and shrinkage estimates for most States, the standard errors of the regression estimates of both poverty and FSP participation rates are smaller than the standard errors of the shrinkage estimates for all but two States-smaller sometimes by more than a half percentage point for standard errors of estimated poverty rates and by more than two percentage points for standard errors of estimated participation rates. Based on these results, we suspect that the estimated standard errors of the regression estimates may overstate the precision of the regression estimates. Our suspicion would seem to be confirmed by our finding that, although the shrinkage estimator is more efficient than the direct sample estimator, the regression estimator cannot be judged more efficient than either the direct sample or shrinkage estimators.

4. Similarities in the Alternative Interval Estimates for Individual States

Although a point estimate is our single best "guess" of the true value of, for example, a State's poverty rate, we do not claim that the State's poverty rate is exactly equal to the point estimate. Thus, we also report a standard error that reflects our uncertainty. Possibly the most meaningful expression of our findings is an interval estimate, that is, a confidence interval, which combines the information from the point estimate and its standard error. We have compared point estimates and standard errors from alternative estimators. We must now compare interval estimates.

To compare interval estimates, we adopt the approach used earlier and assess the overlap in 95 percent confidence intervals. We determine whether the regression and shrinkage methods mainly provide narrower confidence intervals and reduce our uncertainty compared with the direct sample estimation method or whether the regression and shrinkage methods include in confidence intervals values that we may have considered unlikely based on direct sample estimates.

According to Table V.21, the 95 percent confidence interval for the 1988 poverty rate implied by the regression estimator lies entirely within the% percent confidence interval impliedbythe direct sampk estimator for 35 States. At least ten percent of the regression estimator confidence interval lies outside the direct sample estimator confidence interval for 13 States. More than a quarter of the regression estimator confidence interval lies outside the direct sample estimator confidence interval for eight States, and more than half of the regression estimator confidence interval lies outside the direct sample estimator wnfidence interval for four States. For three States, there is no overlap at all.

Although for 15 States the shrinkage estimator confidence interval extends outside the direct sampk estimator confidence interval, the overlap between the shrinkage estimator and direct sampk estimator confidence intervals tends to be substantially greater than the overlap between the regression estimator and direct sample estimator confidence intervals. At least ten percent of the shrinkage estimator confidence interval lies outside the direct sample estimator confidence interval for ten States. However, for only three States does at least a quarter of the shrinkage estimator confidence interval lie outside the direct sample estimator confidence interval, and for only one of the States does more than half of the shrinkage estimator confidence interval lie outside the direct sample estimator confidence interval.[31] The contrast is even more striking when we consider only the States with the most precise direct sample estimates. For seven of the nine States with direct sample estimate standard errors under one percent, the regression estimator confidence intervals lie partly outside the direct sample estimator wnfidence intervals. For five of those nine States, the

[31]We obtain similar results for FSP eligibility rate and FSP participation rate confidence intervals, although regression estimator confidence intervals may tend to extend slightly farther beyond the boundaries of direct sample estimator confidence interval& For example, more than half of the FSP participation rate confidence interval implied by the regression method lies outside the direct sample estimator confidence interval for seven States.

shrinkage estimator confidence intervals lie partly outside the direct sample estimator confidence intervals. Nonoverlap--at least 30 percent for four of the seven regression estimator confidence intervals--is at most 26 percent for the five shrinkage estimator confidence intervals and over 11 percent for only one of the five.

For some States, the regression method and, to a much lesser degree, the shrinkage method produce confidence intervals that include values that are considered unlikely, even according to relatively wide confidence intervals from the direct sample estimation method. For most States, however, the regression and shrinkage methods yield narrow confidence intervals that lie entirely inside the confidence intervals implied by the direct sample estimation method.

5. The Sensitivity of the Alternative Estimates

We conclude our assessment of alternative estimators by reviewing our results on the sensitivity of estimates to choices that we have to make. After we have decided how to determine whether an individual in the CPS is in poverty or eligible for the FSP, the direct sample estimation method requires no additional choices, except how to estimate standard errors.[32] The relative simplicity of the direct sample estimation method and the lack of assumptions underlying the method are advantages.[33] For both the regression and shrinkage methods, we must make more choices. For example, we must specify a model that relates a criterion variable to symptomatic indicators. In a limited sensitivity analysis, we find that similar regression models can produce moderately to substantially different estimates for some States. We also find that shrinkage estimates are much less sensitive to model specification. Combining regression estimates with direct sample estimates dampens the effect of changes in model specification. Finally, although the shrinkage estimator must

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[32]All three estimation methods use the simulation procedure described in Appendix A for determining FSP eligibility status. Assessing the sensitivity of our estimates to the simulation procedure used is beyond the scope of this study. Exploring alternative ways to estimate standard errors is also beyond the scope of this study.

[33]However, the simplicity comes at a cost of substantial imprecision from ignoring the relevant information that variations in both poverty and eligibility rates are systematic.

rely on possibly unreliable direct sample estimator standard errors, the shrinkage estimates do not seem to be sensitive to large errors in the estimated standard errors for direct sample estimates.

TABLE V.1

NUMBER OF INDIVIDUALS IN POVERTY BY STATE, 1986-1988
SAMPLE ESTIMATES
(Thousands of Individuals)

Division/ State	Individuals in Poverty			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	115	139	159	18	21	22
New Hampshire	37	36	73	11	11	16
Vermont	58	50	43	9	9	9
Massachusetts	538	491	497	62	62	48
Rhode Island	87	80	99	16	16	18
Connecticut	186	215	128	40	44	39
Middle Atlantic						
New York	2,322	2,578	2,369	140	153	163
New Jersey	679	661	475	77	80	52
Pennsylvania	1,190	1,225	1,246	104	110	103
East North Central						
Ohio	1,372	1,470	1,356	111	119	101
Indiana	674	622	560	75	76	95
Illinois	1,517	1,654	1,436	119	128	111
Michigan	1,267	1,088	1,112	105	102	87
Wisconsin	501	362	364	76	68	68
West North Central						
Minnesota	517	516	514	68	71	79
Iowa	376	436	263	51	56	45
Missouri	722	717	662	79	82	97
North Dakota	88	80	76	12	12	11
South Dakota	118	113	101	14	14	12
Nebraska	220	202	164	30	30	34
Kansas	269	239	195	42	41	35
South Atlantic						
Delaware	79	48	57	12	10	11
Maryland	414	431	457	60	63	80
District of Columbia	77	79	88	12	13	12
Virginia	547	557	647	84	88	92
West Virginia	432	441	337	41	42	41
North Carolina	884	877	7%	92	%	60
South Carolina	569	511	528	62	62	62
Georgia	879	897	875	91	95	112
Florida	1,342	1,578	1,704	51	58	112

TABLE V.1 (continued)

Division/ State	Individuals in Poverty			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	630	609	634	75	77	78
Tennessee	853	831	883	87	90	102
Alabama	959	849	775	80	79	91
Mississippi	695	650	704	56	57	62
West South Central						
Arkansas	499	533	527	50	53	55
Louisiana	953	1,087	968	81	88	101
Oklahoma	469	540	543	56	61	65
Texas	2,825	2,767	3,006	167	172	176
Mountain						
Montana	136	147	116	16	17	15
Idaho	180	142	124	20	19	18
Wyoming	73	49	43	10	9	8
Colorado	426	407	405	54	55	62
New Mexico	306	292	343	30	31	32
Arizona	484	431	491	58	57	67
Utah	209	174	162	27	26	27
Nevada	82	108	93	15	18	18
Pacific						
Washington	563	516	402	75	75	73
Oregon	332	356	285	48	51	51
California	3,453	3,508	3,687	175	183	259
Alaska	59	59	53	7	7	8
Hawaii	109	98	117	17	17	19
Median State	484	441	457	56	57	60
united States	32,370	32,546	31,745	[a]	[a]	[a]

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.2

NUMBER OF INDIVIDUALS ELIGIBLE FOR THE FSP BY STATE, 1986-1988
SAMPLE ESTIMATES
(Thousands of Individuals)

Division/ State	Individuals Eligible for the FSP			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	156	165	174	21	22	23
New Hampshire	49	61	91	12	14	18
Vermont	67	55	54	10	9	10
Massachusetts	654	595	636	68	68	53
Rhode Island	116	101	115	18	18	19
Connecticut	246	254	179	45	48	46
Middle Atlantic						
New York	2,804	2,979	2,863	152	162	176
New Jersey	792	712	586	83	82	58
Pennsylvania	1,414	1,499	1,627	112	120	116
East North Central						
Ohio	1,618	1,617	1,675	119	123	110
Indiana	834	765	627	82	83	100
Illinois	1,843	1,897	1,620	129	136	117
Michigan	1,345	1,217	1,146	108	107	88
Wisconsin	580	468	382	81	76	70
West North Central						
Minnesota	569	564	535	71	74	80
Iowa	455	454	327	55	57	49
Missouri	779	767	723	82	85	101
North Dakota	91	75	73	12	12	11
South Dakota	135	144	101	14	15	12
Nebraska	287	217	219	33	31	38
Kansas	336	306	293	46	46	42
South Atlantic						
Delaware	102	66	73	13	11	12
Maryland	569	459	469	69	65	81
District of Columbia	95	89	88	13	13	12
Virginia	661	691	757	91	97	98
West Virginia	560	523	394	44	45	44
North Carolina	1,148	1,086	1,027	102	104	67
South Carolina	674	645	646	67	68	67
Georgia	1,179	1,085	1,075	102	103	121
Florida	1,672	1,949	1,921	56	63	117

TABLE V.2 (continued)

Division/ State	Individuals Eligible for the FSP 1986	1987	1988	Standard Errors 1986	1987	1988
East South Central						
Kentucky	813	783	825	82	85	86
Tennessee	1,062	1,033	1,096	95	98	110
Alabama	1,135	1,091	1,042	84	87	101
Mississippi	889	814	802	60	61	65
West South Central						
Arkansas	615	624	603	54	56	57
Louisiana	1,153	1,150	1,181	86	89	108
Oklahoma	593	710	695	61	68	71
Texas	3,477	3,302	3,304	181	184	183
Mountain						
Montana	140	155	128	16	18	16
Idaho	186	180	164	20	21	20
Wyoming	81	51	49	10	9	9
Colorado	509	441	487	58	57	67
New Mexico	319	342	405	30	33	34
Arizona	589	545	516	62	63	69
Utah	244	242	234	29	30	31
Nevada	%	151	125	16	21	20
Pacific						
Washington	698	560	466	82	78	78
Oregon	381	415	398	51	55	59
California	4,108	4,061	4,097	188	195	271
Alaska	91	82	71	9	9	9
Hawaii	154	132	149	19	19	21
Median state	580	545	487	60	63	65
united states	39,163	38,370	37,333	[a]	[a]	[a]

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.3

ADJUSTED INDIVIDUAL FSP PARTICIPATION RATES BY STATE, 1986-1988
SAMPLE ESTIMATES
(Percent)

Division/ State	Adjusted FSP Participation Rates 1986	1987	1988	Standard Errors 1986	1987	1988
New England						
Maine	67.1	55.2	46.5	9.8	8.1	6.2
New Hampshire	43.3	29.9	20.4	10.9	7.0	4.1
Vermont	51.5	60.1	59.9	8.2	11.0	10.8
Massachusetts	46.4	48.9	47.4	5.1	5.9	4.0
Rhode Island	53.0	57.5	47.6	8.8	10.7	7.9
Connecticut	49.4	43.4	60.1	9.4	8.5	15.3
Middle Atlantic						
New York	57.4	53.0	51.0	3.4	3.2	3.1
New Jersey	52.4	50.5	59.1	5.8	6.1	5.8
Pennsylvania	68.9	61.5	56.2	5.8	5.3	4.0
East North Central						
Ohio	65.9	65.0	61.5	5.2	5.4	4.1
Indiana	40.5	39.5	44.5	4.3	4.6	7.1
Illinois	57.1	53.7	61.3	4.4	4.2	4.4
Michigan	65.4	69.8	74.7	5.7	6.6	5.8
Wisconsin	58.8	68.5	76.5	8.7	11.8	14.0
West North Central						
Minnesota	39.2	40.2	44.0	5.3	5.6	6.6
Iowa	43.9	40.9	49.9	5.8	5.6	7.5
Missouri	46.7	47.9	529	5.3	5.7	7.4
North Dakota	39.0	44.2	49.4	5.7	7.4	7.1
South Dakota	39.4	35.9	49.4	4.6	4.3	5.8
Nebraska	33.0	43.9	41.2	4.2	6.7	7.2
Kansas	34.0	38.4	39.8	5.0	6.1	5.7
South Atlantic						
Delaware	28.7	40.9	38.9	4.0	7.3	6.3
Maryland	44.8	51.9	47.7	5.8	7.8	8.2
District of Columbia	65.1	63.6	64.5	10.0	10.5	9.1
Virginia	49.3	44.4	425	7.2	6.6	5.5
West Virginia	46.0	48.0	62.5	4.3	4.8	7.0
North Carolina	36.7	35.7	36.8	3.6	3.8	2.4
South Carolina	43.9	40.5	38.5	4.9	4.8	4.0
Georgia	40.2	41.5	42.5	3.9	4.3	4.8
Florida	35.1	30.4	324	1.3	1.1	2.0

TABLE V.3 (continued)

Division/ State	Adjusted FSP Participation Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	63.0	S8.8	55.7	7.2	7.2	5.8
Tennessee	45.6	45.5	43.6	4.6	4 3	4.4
Alabama	40.5	38.6	39.6	3 5	3.6	3.8
Mississippi	533	59.8	59.6	4.4	5.4	4.8
West South Central						
Arkansas	373	3S.7	36.5	3.8	3.7	3 5
Louisiana	58.2	61.4	59.3	5.1	5.6	5.4
Oklahoma	428	37.6	36.8	4.9	4.1	3.8
Texas	37.9	43.0	43.9	2.2	2.7	2 4
Mountain						
Montana	40.2	36.5	421	5.2	4.6	5.3
Idaho	30.9	32.0	36.1	3.8	4.1	4.4
Wyoming	33.5	51.5	520	4.7	9.5	9.5
Colorado	35.1	43.0	41.2	4.4	6.0	5.7
New Mexico	46.5	42.9	33.6	5.0	4.7	2.8
Arizona	32.8	37.3	46.6	3.8	4.7	6.2
Utah	31.8	35.1	38.2	4.1	4.7	5.1
Nevada	34.9	22.0	29.7	6.2	3.2	4.9
Pacific						
Washington	40.8	51.3	63.8	5.2	7.6	10.7
Oregon	56.2	47.9	49.5	8.1	6.9	7 3
California	37.8	38.1	38.8	1.9	2.0	2 6
Alaska	28.7	35.4	34.9	3.0	4.0	4.7
Hawaii	57.5	62.0	51.8	7.8	9.5	7.2
Median State	43.9	43.9	46.6	5.0	5.6	5.7
United States	47.1	47.0	48.0	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989. FSP participation counts are from Food Stamp Program Statistical Summary of Operations data, adjusted for errors in issuance.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.4

INDIVIDUAL POVERTY RATES BY STATE, 1986-1988
SAMPLE ESTIMATES
(Percent)

Division/ State	Poverty Rates 1986	1987	1988	Standard Errors 1986	1987	1988
New England						
Maine	10.2	120	13.2	1.6	1.8	1.9
New Hampshire	3.7	3.4	6.7	1.0	1.0	1.5
Vermont	11.0	9.5	8.1	1.8	1.7	1.7
Massachusetts	9.2	8.4	85	1.1	1.1	0.8
Rhode Island	9.1	8.2	9.8	1.7	1.6	1.8
Connecticut	6.0	6.9	4.0	1.3	1.4	1.2
Middle Atlantic						
New York	13.2	14.6	13.4	0.8	0.9	0.9
New Jersey	8.9	8.7	6.2	1.0	1.1	0.7
Pennsylvania	10.1	10.4	10.3	0.9	0.9	0.8
East North Central						
Ohio	12.8	13.7	12.4	1.0	1.1	0.9
Indiana	12.7	11.4	10.1	1.4	1.4	1.7
Illinois	13.3	14.3	12.7	1.0	1.1	1.0
Michigan	13.9	12.2	12.1	1.2	1.1	0.9
Wisconsin	10.7	7.7	7.8	1.6	1.4	1.5
West North Central						
Minnesota	125	120	11.6	1.7	1.7	1.8
Iowa	129	15.0	9.4	1.7	1.9	1.6
Missouri	14.4	14.1	127	1.6	1.6	1.9
North Dakota	13.5	123	11.6	1.9	1.9	1.6
South Dakota	17.0	15.9	14.2	1.9	20	1.7
Nebraska	13.6	125	10.3	1.8	1.8	21
Kansas	11.1	9.9	8.1	1.7	1.7	1.5
South Atlantic						
Delaware	12.4	7.5	8.6	1.8	1.5	1.6
Maryland	9.2	9.5	9.8	1.3	1.4	1.7
District of Columbia	12.8	13.9	15.2	2.0	2.2	2.1
Virginia	9.7	9.6	10.8	1.5	1.5	1.5
West Virginia	22.4	23.1	17.9	2.1	2.2	2.2
North Carolina	14.3	14.1	12.6	1.5	1.5	0.9
South Carolina	17.3	15.5	15.5	1.9	1.9	1.8
Georgia	14.6	14.9	14.0	1.5	1.6	1.8
Florida	11.4	12.9	13.6	0.4	0.5	0.9

TABLE V.4 (continued)

Division/ State	Poverty Rates 1986	1987	1988	Standard Errors 1986	1987	1988
East South Central						
Kentucky	17.7	167	17.6	21	21	22
Tennessee	183	17.5	18.0	1.9	1.9	21
Alabama	23.8	21.2	193	20	20	23
Mississippi	26.6	25.5	27.2	21	22	24
West South Central						
Arkansas	213	221	21.6	21	22	22
Louisiana	220	25.1	228	1.9	20	24
Oklahoma	14.7	169	173	1.7	1.9	21
Texas	173	16.9	18.0	1.0	1.1	1.1
Mountain						
Montana	16.5	183	14.6	20	22	1.9
Idaho	18.5	143	12.5	21	1.9	L8
Wyoming	14.6	10.8	9.6	20	1.9	1.9
Colorado	13.5	127	125	1.7	1.7	1.9
New Mexico	21.3	19.8	23.0	21	21	21
Arizona	14.3	125	14.1	1.7	1.7	1.9
Utah	126	10.5	9.8	1.6	1.6	1.6
Nevada	8.1	105	8.6	1.5	1.7	1.7
Pacific						
Washington	129	11.5	8.7	1.7	1.7	1.6
Oregon	123	13.1	10.4	1.8	1.9	1.9
California	127	126	13.2	0.6	0.7	0.9
Alaska	11.4	115	11.0	1.4	1.5	1.7
Hawaii	10.7	9.0	11.1	1.6	1.5	1.8
Median State	12.9	12.6	12.4	1.7	1.7	1.7
United States	13.6	13.5	13.0	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates,

TABLE V.5

INDIVIDUAL FSP ELIGIBILITY RATES BY STATE, 1986-1988
SAMPLE ESTIMATES
(Percent)

Division/ State	FSP Eligibility Rates			standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	13.9	143	14.5	1.9	1.9	1.9
New Hampshire	4.9	5.8	83	L2	13	1.7
Vermont	12.7	103	10.1	1.9	1.8	1.8
Massachusetts	IL2	10.2	10.9	L2	1.2	0.9
Rhode Island	12.2	10.2	11.4	1.9	1.8	1.9
Connecticut	7.9	8.1	5.6	1.4	1.5	1.4
Middle Atlantic						
New York	15.9	16.9	16.2	0.9	0.9	1.0
New Jersey	10.4	9.4	7.7	1.1	1.1	0.8
Pennsylvania	120	127	13.4	1.0	1.0	1.0
East North Central						
Ohio	15.1	15.1	15.4	1.1	1.2	1.0
Indiana	15.7	14.0	11.3	1.5	1.5	1.8
Illinois	16.1	16.4	14.3	1.1	1.2	1.0
Michigan	14.8	13.6	124	1.2	1.2	1.0
Wisconsin	124	9.9	8.1	1.7	1.6	1.5
West North Central						
Minnesota	13.8	13.1	12.1	1.7	1.7	1.8
Iowa	15.7	15.6	11.6	1.9	20	1.7
Missouri	15.6	15.0	13.9	1.6	1.7	1.9
North Dakota	14.0	11.6	113	1.9	1.8	1.6
south Dakota	193	203	14.2	20	21	1.7
Nebraska	17.7	13.4	13.7	20	1.9	24
Kansas	13.8	12.6	122	1.9	1.9	1.8
South Atlantic						
Delaware	16.0	10.5	11.1	20	1.8	1.8
Maryland	126	10.1	10.1	15	1.4	1.7
District of Columbia	15.8	15.6	15.2	22	24	2.1
Virginia	11.8	11.9	127	1.6	1.7	1.6
West Virginia	29.1	27.4	21.0	23	23	23
North Carolina	18.6	17.5	16.3	1.7	1.7	1.1
South Carolina	20.5	195	19.0	20	21	2.0
Georgia	19.6	18.0	17.3	1.7	1.7	1.9
Florida	14.2	15.9	15.4	05	0.5	0.9

TABLE V.5 (continued)

Division/ State	FSP Eligibility Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	22.8	21.4	22.9	2.3	2.3	24
Tennessee	22.8	21.8	22.4	2.0	21	22
Alabama	28.2	273	25.9	21	22	2.5
Mississippi	34.1	31.9	3Lo	23	24	2.5
West South Central						
Arkansas	26.3	25.9	24.7	2.3	2.3	2.3
Louisiana	26.6	26.6	27.8	20	21	2.5
Oklahoma	18.6	222	221	1.9	21	2.3
Texas	21.2	20.2	19.8	1.1	1.1	1.1
Mountain						
Montana	17.1	19.4	16.1	2.0	22	20
Idaho	19.1	18.1	16.5	21	21	20
Wyoming	16.2	11.1	10.7	21	1.9	2.0
Colorado	16.1	13.7	15.0	1.8	1.8	21
New Mexico	223	23.2	27.1	2.1	2.2	23
Arizona	17.4	15.8	14.8	1.8	1.8	2.0
Utah	14.7	14.5	14.1	1.7	1.8	1.9
Nevada	95	14.7	11.5	1.6	20	1.9
Pacific						
Washington	16.0	125	10.1	1.9	1.7	1.7
Oregon	14.1	153	14.6	1.9	20	22
California	15.2	14.6	14.7	0.7	0.7	1.0
Alaska	17.6	16.0	14.7	1.7	1.7	20
Hawaii	15.0	12.2	14.2	1.9	1.7	20
Median State	15.8	15.0	143	1.9	1.8	1.9
United States	16.4	15.9	153	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.6

STANDARD ERRORS OF INDIVIDUAL POVERTY COUNTS BY STATE, 1986-1988 SAMPLE ESTIMATES

(Thousands of Individuals)

Division/ State	Standard Errors Estimated Using the Direct Method			Standard Errors Estimated Using the Indirect Method		
	1986	1987	1988	1986	1987	1988
New England						
Maine	19	22	24	18	21	22
New Hampshire	11	11	17	11	11	16
Vermont	10	10	9	9	9	9
Massachusetts	65	65	50	62	62	48
Rhode Island	17	17	19	16	16	18
Connecticut	41	46	40	40	44	39
Middle Atlantic						
New York	150	164	174	140	153	163
New Jersey	81	83	54	77	80	52
Pennsylvania	110	116	108	104	110	103
East North Central						
Ohio	118	127	107	111	119	101
Indiana	80	80	100	75	76	95
Illinois	127	138	118	119	128	111
Michigan	113	109	93	105	102	87
Wisconsin	80	71	71	76	68	68
West North Central						
Minnesota	73	76	83	68	71	79
Iowa	54	61	47	51	56	45
Missouri	85	89	104	79	82	97
North Dakota	13	13	11	12	12	11
South Dakota	15	15	13	14	14	12
Nebraska	32	32	35	30	30	34
Kansas	44	43	37	42	41	35
South Atlantic						
Delaware	12	10	11	12	10	11
Maryland	63	67	84	60	63	80
District of Columbia	13	14	13	12	13	12
Virginia	88	93	97	84	88	92
West Virginia	46	48	46	41	42	41
North Carolina	99	103	64	92	96	60
South Carolina	69	68	68	62	62	62
Georgia	98	103	120	91	95	112
Florida	54	61	119	51	58	112

TABLE V.6 (continued)

Division/ State	Standard Errors Estimated Using the Direct Method			Standard Errors Estimated Using the Indirect Method		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	82	84	86	75	77	78
Tennessee	96	99	112	87	90	102
Alabama	91	89	101	80	79	91
Mississippi	65	66	73	56	57	62
West South Central						
Arkansas	56	60	62	50	53	55
Louisiana	91	101	114	81	88	101
Oklahoma	60	67	71	56	61	65
Texas	182	188	193	167	172	176
Mountain						
Montana	18	19	17	16	17	15
Idaho	22	21	19	20	19	18
Wyoming	11	9	9	10	9	8
Colorado	58	59	66	54	55	62
New Mexico	34	34	36	30	31	32
Arizona	62	61	73	58	57	67
Utah	29	27	28	27	26	27
Nevada	16	19	19	15	18	18
Pacific						
Washington	80	80	77	75	75	73
Oregon	51	55	54	48	51	51
California	186	19s	276	175	183	259
Alaska	8	8	9	7	7	8
Hawaii	18	17	20	17	17	19
Median State	60	61	64	57	57	60
United States	a	a	a	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors fix the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.7

STANDARD ERRORS OF INDIVIDUAL FSP ELIGIBILITY COUNTS BY STATE, 1986-1988
SAMPLE ESTIMATES
(Thousands of Individuals)

Division/ State	Standard Errors Estimated Using the Direct Method			Standard Errors Estimated Using the Indirect Method		
	1986	1987	1988	1986	1987	1988
New England						
Maine	23	24	25	21	22	23
New Hampshire	12	14	19	12	14	18
Vermont	11	10	10	10	9	10
Massachusetts	72	71	56	68	68	53
Rhode Island	19	19	20	18	18	19
- c u t	47	50	47	45	48	46
Middle Atlantic						
New York	165	177	191	152	162	176
New Jersey	87	86	60	83	82	58
Pennsylvania	119	128	124	112	120	116
East North Central						
Ohio	128	133	119	119	123	110
Indiana	89	89	106	82	83	100
Illinois	140	148	126	129	136	117
Michigan	116	115	94	108	107	88
Wisconsin	86	81	73	81	76	70
West North Central						
Minnesota	77	79	85	71	74	80
Iowa	60	62	52	55	57	49
Missouri	89	92	109	82	85	101
North Dakota	13	13	11	12	12	11
South Dakota	16	17	13	14	15	12
Nebraska	36	33	41	33	31	38
Kansas	49	49	45	46	46	42
South Atlantic						
Delaware	14	12	13	13	11	12
Maryland	74	69	85	69	65	81
District of Columbia	15	15	13	13	13	12
Virginia	97	103	105	91	97	98
West Virginia	52	53	49	44	4s	44
North Carolina	113	11s	72	102	104	67
South Carolina	7s	76	75	67	68	67
Georgia	113	113	133	102	103	121
Florida	61	68	127	56	63	117

TABLE V.7 (continued)

Division/ State	Standard Errors Estimated Using the Direct Method			Standard Errors Estimated Using the Indirect Method		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	93	95	98	82	85	86
Tennessee	108	110	125	95	98	110
Alabama	99	101	117	84	87	101
Mississippi	74	73	78	60	61	65
West South Central						
Arkansas	62	65	66	54	56	57
Louisiana	100	104	126	86	89	108
Oklahoma	68	77	81	61	68	71
Texas	202	205	202	181	184	183
Mountain						
Montana	18	20	18	16	18	16
Idaho	23	23	22	20	21	20
Wyoming	11	9	9	10	9	9
Colorado	63	61	73	58	57	67
New Mexico	35	37	40	30	33	34
Arizona	69	69	74	62	63	69
Utah	31	32	34	29	30	31
Nevada	17	22	22	16	21	20
Pacific						
Washington	89	83	82	82	78	78
Oregon	55	60	64	51	55	59
California	202	209	290	188	195	271
Alaska	9	9	10	9	9	9
Hawaii	21	20	22	19	19	21
Median State	55	60	52	51	55	49
United States	a	a	a	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.8

INDIVIDUAL POVERTY RATES BY STATE, 1986-1988
REGRESSION ESTIMATES
(Percent)

Division/ State	Poverty Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	11.7	11.1	13.1	0.8	1.0	0.4
New Hampshire	4.4	3.8	5.0	0.9	1.0	0.7
Vermont	11.0	10.3	124	0.8	1.0	03
Massachusetts	6.7	7.1	9.6	0.9	1.0	0.6
Rhode Island	9.3	9.2	11.8	0.8	0.9	03
Connecticut	6.3	6.0	4.2	0.7	0.8	0.8
Middle Atlantic						
New York	123	12.5	11.8	0.5	0.6	0.5
New Jersey	7.9	8.1	6.5	0.6	0.7	0.7
Pennsylvania	13.0	12.4	10.6	03	03	0.5
East North Central						
Ohio	13.0	125	11.0	03	0.4	03
Indiana	129	12.1	10.2	0.4	0.4	0.4
Illinois	11.6	11.1	103	03	0.4	03
Michigan	124	121	11.4	03	0.4	0.4
Wisconsin	13.9	13.4	123	0.3	0.3	03
West North Central						
Minnesota	10.8	10.0	8.6	0.4	0.5	0.4
Iowa	13.0	124	10.8	0.4	0.4	0.4
Missouri	13.9	13.4	123	0.3	0.3	0.3
North Dakota	14.0	13.0	11.6	0.4	0.5	0.6
South Dakota	15.1	14.2	121	0.4	0.5	0.5
Nebraska	125	11.7	9.9	0.4	0.5	0.4
Kansas	11.5	10.9	9.4	0.4	0.4	0.4
South Atlantic						
Delaware	11.4	10.8	9.4	03	0.4	03
Maryland	9.7	9.3	8.1	0.4	0.5	0.4
District of Columbia	12.0	13.1	14.1	0.8	0.9	1.0
Virginia	121	11.6	10.0	03	0.4	0.4
West Virginia	19.2	18.5	16.8	0.5	0.6	0.6
North Carolina	17.0	163	15.4	0.4	0.4	03
South Carolina	192	18.6	17.7	0.5	0.5	0.5
Georgia	16.7	16.5	16.1	0.4	0.5	0.4
Florida	13.2	127	13.4	0.3	03	0.8

TABLE V.8 (continued)

Division/ State	Poverty Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	19.5	193	179	0.5	0.6	0.6
Tennessee	18.7	18.2	173	0.5	0.5	0.5
Alabama	20.7	20.5	20.0	0.6	0.7	0.6
Mississippi	253	25.4	25.0	0.9	LO	LO
West South Central						
Arkansas	20.8	20.7	20.0	0.6	0.7	0.6
Louisiana	22.4	22.5	23.2	0.8	0.9	0.8
Oklahoma	18.5	18.2	18.2	0.7	0.8	0.7
Texas	16.8	16.6	17.5	0.7	0.8	0.8
Mountain						
Montana	14.6	13.6	11.9	0.5	0.5	0.5
Idaho	14.9	13.3	11.2	0.6	0.6	0.5
Wyoming	14.7	13.8	12.6	0.8	0.9	0.8
Colorado	13.5	13.3	13.2	0.7	0.8	0.7
New Mexico	19.7	19.0	19.6	0.7	0.8	0.8
Arizona	129	12.0	11.9	0.3	0.4	0.7
Utah	14.3	12.6	11.1	0.6	0.7	0.7
Nevada	10.5	9.8	8.6	0.4	0.4	0.5
Pacific						
Washington	11.6	11.4	11.1	03	0.4	0.5
Oregon	13.2	121	11.4	0.4	0.4	0.6
California	13.5	14.s	14.8	0.6	0.7	0.6
Alaska	93	10.2	9.9	0.9	1.0	0.9
Hawaii	11.8	11.1	103	03	0.4	0.4
Median State	13.0	12.5	11.8	0.5	0.5	05
United States	13.8	13.6	13.0	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from Match Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totais implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.9

INDIVIDUAL FSP ELIGIBILITY RATES BY STATE, 1986-1988
REGRESSION ESTIMATES
(Percent)

Division/ State	FSP Eligibility Rates 1986	1987	1988	Standard Errors 1986	1987	1988
New England						
Maine	14.4	13.6	143	1.0	1.1	1.0
New Hampshire	5.6	4.7	5.4	1.1	1.1	1.1
Vermont	13.6	12.5	13.2	LO	Ll	LO
Massachusetts	9.4	8.7	10.2	1.1	1.1	1.1
Rhode Island	11.8	11.2	12.1	1.0	1.0	LO
Connecticut	8.4	7.0	63	0.9	0.9	0.9
Middle Atlantic						
New York	15.7	14.9	14.1	0.6	0.7	0.6
New Jersey	10.3	9.5	8.7	0.8	0.8	0.8
Pennsylvania	15.7	14.8	13.9	0.4	0.4	0.4
East North Central						
Ohio	15.4	14.9	13.5	0.4	0.4	0.4
Indiana	15.0	14.3	126	0.5	0.5	0.5
Illinois	14.1	13.2	124	0.4	0.4	0.4
Michigan	15.1	14.4	13.3	0.4	0.4	0.4
Wisconsin	16.8	16.0	15.4	0.4	0.4	0.4
West North Central						
Minnesota	12.8	11.8	10.9	0.5	0.5	05
Iowa	15.2	14.8	13.4	0.5	0.5	05
Missouri	16.8	16.0	14.9	0.4	0.4	0.4
North Dakota	16.2	15.5	14.7	0.5	0.6	0.6
South Dakota	17.5	16.9	15.5	0.6	0.5	05
Nebraska	14.6	13.9	123	0.5	0.5	0.5
Kansas	13.6	129	115	0.5	0.5	0.5
South Atlantic						
Delaware	13.9	12.8	11.7	0.4	0.4	0.4
Maryland	121	11.0	10.1	0.6	0.6	0.6
District of Columbia	16.0	15.6	15.3	1.0	1.0	1.0
Virginia	14.8	13.8	128	0.4	0.4	0.4
West Virginia	22.9	22.2	21.2	0.6	0.6	0.6
North Carolina	20.6	19.6	18.4	0.4	0.4	0.4
South Carolina	23.2	22.3	20.7	0.6	0.6	0.5
Georgia	20.6	19.8	18.6	0.5	0.5	05
Florida	16.0	15.1	14.1	0.4	0.4	0.4

TABLE V.9 (continued)

Division/ State	FSP Eligibility Rates 1986	1987	1988	Standard Errors 1986	1987	1988
East South Central						
Kentucky	23.7	23.2	22.1	0.6	0.6	0.6
Tennessee	22.9	21.9	20.9	0.6	0.6	0.5
Alabama	25.4	24.7	23.9	0.7	0.7	0.7
Mississippi	313	30.7	30.1	1.1	1.2	1.1
West South Central						
Arkansas	25.5	24.9	23.9	0.7	0.7	0.7
Louisiana	27.5	26.7	27.5	1.0	1.1	LO
Oklahoma	22.3	21.4	21%	0.9	0.9	0.8
Texas	20.3	195	193	0.8	0.9	0.8
Mountain						
Montana	16.8	16.2	14.4	0.6	0.6	0.6
Idaho	17.0	15.9	13.6	0.7	0.7	0.6
Wyoming	17.0	16.0	16.1	1.0	1.0	0.9
Colorado	16.3	15.4	16.0	0.9	0.9	0.9
New Mexico	23.6	22.4	229	0.9	0.9	0.9
Arizona	15.2	14.3	129	0.4	0.5	0.4
Utah	16.0	15.0	126	0.8	0.8	0.7
Nevada	12.6	11.6	10.0	0.5	0.5	0.5
Pacific						
Washington	13.9	13.6	124	0.4	0.4	0.4
Oregon	15.4	14.4	126	0.5	0.5	0.5
California	17.6	17.4	17.4	0.8	0.8	0.7
Alaska	11.7	11.6	13.1	1.1	1.1	1.0
Hawaii	14.1	13.2	12.1	0.4	0.4	0.4
Median State	15.7	14.9	13.9	0.6	0.6	0.6
United States	16.9	16.1	15.5	[a]	[a]	[a]

SOURCE Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable Thus, we do not report standard errors for any national estimates.

TABLE V.10

NUMBER OF INDIVIDUALS IN POVERTY BY STATE, 1986-1988
REGRESSION ESTIMATES
('Thousands of Individuals)

Division/ State	Individuals in Poverty			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	132	128	157	9	12	5
New Hampshire	45	40	54	9	10	8
Vermont	58	55	66	4	5	2
Massachusetts	395	416	562	53	58	35
Rhode Island	89	90	119	8	9	3
Connecticut	198	189	136	22	25	26
Middle Atlantic						
New York	2,163	2,193	2,084	88	106	88
New Jersey	600	609	4%	46	53	53
Pennsylvania	1,536	1,464	1,287	35	35	61
East North Central						
Ohio	1,389	1,341	1,202	32	43	33
Indiana	685	657	562	21	22	22
Illinois	1,322	1,281	1,173	34	46	34
Michigan	1,130	1,082	1,051	27	36	37
Wisconsin	654	635	579	14	14	14
West North Central						
Minnesota	447	431	382	17	22	18
Iowa	378	360	304	12	12	11
Missouri	6%	685	641	15	15	16
North Dakota	91	84	76	3	3	4
South Dakota	105	101	85	3	4	4
Nebraska	203	189	158	6	8	6
Kansas	280	265	226	10	10	10
South Atlantic						
Delaware	73	69	62	2	3	2
Maryland	438	423	379	18	23	19
District of Columbii	72	75	82	5	5	6
Virginia	679	674	595	17	23	24
west Virginia	370	352	316	10	11	11
North Carolina	1,049	1,016	970	25	25	19
South Carolina	630	613	603	16	17	17
Georgia	1,004	994	1,001	24	30	25
Florida	1,551	1,556	1,670	35	37	100

TABLE V.10 (continued)

Division/ State	Individuals in Poverty			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	694	704	644	18	22	22
Tennessee	869	864	849	23	24	25
Alabama	833	821	804	24	28	24
Mississippi	660	647	647	23	26	26
West South Central						
Arkansas	488	498	488	14	17	15
Louisiana	973	975	984	35	39	34
Oklahoma	589	582	572	22	26	22
Texas	2,744	2,716	2,920	115	131	133
Mountain						
Montana	120	109	95	4	4	4
Idaho	145	132	111	6	6	5
Wyoming	73	63	57	4	4	4
Colorado	426	426	426	22	26	23
New Mexico	282	280	294	10	12	12
Arizona	437	415	415	10	14	24
Utah	237	209	184	10	12	12
Nevada	106	101	94	4	4	5
Pacific						
Washington	509	514	514	13	18	23
Oregon	356	329	312	11	11	16
California	3,667	4,035	4,111	162	195	167
Alaska	48	52	47	5	5	4
Hawaii	121	120	108	3	4	4
Median State	438	426	426	15	17	18
United States	32,839	32,657	31,751	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates

TABLE V.ll

NUMBER OF INDIVIDUALS ELIGIBLE FOR THE FSP BY STATE, 1986-1988
REGRESSION ESTIMATES
(Thousands of Individuals)

Division/ State	Individuals Eligible for the FSP			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	162	157	172	11	13	12
New Hampshire	56	49	58	11	12	12
Vermont	72	67	70	S	6	S
Massachusetts	551	510	598	64	64	64
Rhode Island	112	110	122	10	10	10
Connecticut	262	219	200	28	28	29
Middle Atlantic						
New York	2,768	2,617	2,494	106	123	106
New Jersey	782	716	664	61	60	61
Pennsylvania	1,847	1,743	1,685	47	47	48
East North Central						
Ohio	1,647	15%	1,470	43	43	44
Indiana	795	780	698	27	27	28
Illinois	1,610	1,521	1,411	46	46	45
Michigan	1371	1,287	1,224	36	36	37
Wisconsin	790	758	722	19	19	19
West North Central						
Minnesota	528	So9	484	21	22	22
Iowa	442	429	376	1s	1s	14
Missouri	840	817	775	20	20	21
North Dakota	105	101	%	3	4	4
South Dakota	122	120	109	4	4	4
Nebraska	236	225	1%	8	8	8
Kansas	331	314	276	12	12	12
South Atlantic						
Delaware	88	81	77	3	3	3
Maryland	546	500	469	27	27	28
District of Columbia	%	89	88	6	6	6
Virginia	834	801	764	22	23	24
west Virginia	442	423	398	12	11	11
North Carolina	1,270	1,218	1,160	25	25	25
south Carolina	763	736	705	20	20	17
Georgia	1,240	1,193	1,157	30	30	31
Florida	1,889	1,854	1,760	47	49	So

TABLE V.ll (continued)

Division/ State	Individuals Eligible for the FSP			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	842	847	797	21	22	22
Tennessee	1,063	1,039	1,024	28	28	25
Alabama	1,024	990	960	28	28	28
Mississippi	817	783	779	W	31	28
West South Central						
Arkansas	596	600	585	16	17	17
Louisiana	1,192	1,155	1,169	43	48	42
Oklahoma	709	684	686	29	29	25
Texas	3323	3,181	3319	131	147	133
Mountain						
Montana	138	129	114	5	5	5
Idaho	166	158	135	7	7	6
Wyoming	84	73	73	5	5	4
Colorado	516	493	517	28	29	29
New Mexico	338	330	342 --	13	13	13
Arizona	515	493	450	14	17	14
Utah	266	249	209	13	13	12
Nevada	127	119	108	5	5	5
Pacific						
Washington	609	610	572	17	18	18
Oregon	415	391	343	14	14	14
California	4,756	4,834	4,841	217	223	195
Alaska	61	60	63	6	6	5
Hawaii	145	142	127	4	4	4
Median State	546	509	517	m	m	19
United States	40,300	38,898	37,692	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.12

ADJUSTED INDIVIDUAL FSP PARTICIPATION RATES BY STATE, 1986-1988
REGRESSION ESTIMATES
(Percent)

Division/ State	Adjusted FSP Participation Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	64.6	58.1	47.2	4.5	4.7	3.3
New Hampshire	373	36.9	31.8	7.4	8.7	6.5
Vermont	48.1	49.2	45.6	3.6	4 3	3.5
Massachusetts	55.1	57.1	so.4	6.4	7.2	5.4
Rhode Island	54.7	524	44.9	4.6	4.7	3.7
Connecticut	46.5	50.2	53.8	5.0	6.5	7.7
Middle Atlantic						
New York	58.2	60.4	58.6	2.2	2 9	25
New Jersey	53.0	50.3	52.1	4.1	4.2	4.8
Pennsylvania	52.7	52.9	54.2	1.4	1.5	L6
East North Central						
Ohio	64.8	65.9	70.1	1.7	1.8	21
Indiana	42.5	38.7	40.0	1.4	1.4	lb
Illinois	65.4	66.9	703	1.9	2 0	2.3
Michigan	64.1	66.0	70.0	1.7	1.8	21
Wisconsin	43.2	42.3	40.5	1.1	1.1	1.1
West North Central						
Minnesota	42.3	44.5	48.6	1.7	1.9	22
Iowa	45.2	433	43.4	1.5	1.5	1.6
Missouri	433	45.0	493	1.0	1.1	13
North Dakota	33.9	33.2	37.6	1.1	13	1.5
South Dakota	43.4	43.1	45.5	1.5	13	1.5
Nebraska	40.1	42.5	46.0	1.4	1.6	L9
Kansas	34.5	37.4	42.3	13	15	1.8
South Atlantic						
Delaware	33.2	33.3	36.9	1.0	1.1	1.3
Maryland	46.7	47.7	47.7	2.3	2 6	2.8
District of Columbia	64.1	63.4	64.4	4.0	4.1	4.2
Virginia	39.1	383	42.1	1.1	1.1	1.3
West Virginia	58.3	593	61.9	1.6	1.6	L8
North Carolina	33.2	31.8	326	0.7	0.7	a7
South Carolina	38.8	35.5	353	1.0	1.0	03
Georgia	38.2	37.7	39.5	1.0	1.0	1.1
Florida	31.0	32.0	35.4	0.8	0.9	Lo

TABLE V.12 (continued)

Division/ State	Adjusted FSP Participation Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	60.8	54.3	57.6	1.6	1.4	1.6
Tennessee	45.5	45.2	46.6	1.2	13	1.1
Alabama	44.9	426	43.0	13	1.2	13
Mississippi	58.1	622	61.4	21	2.5	23
West South Central						
Arkansas	38.5	37.2	37.6	1.1	1.1	1.1
Louisiana	56.3	61.1	59.9	21	2s	22
Oklahoma	35.8	39.0	373	1.5	1.7	1.4
Texas	39.6	44.7	43.7	1.6	21	1.8
Mountain						
Montana	40.8	43.9	47.0	1.5	1.6	20
Idaho	34.6	36.6	43.9	1.4	1.6	1.9
Wyoming	321	35.5	34.8	1.9	22	20
Colorado	34.6	38.5	38.8	1.9	23	22
New Mexico	44.0	44.4	39.8	1.7	1.8	1.6
Arizona	37.6	41.2	53.4	1.0	1.4	1.7
Utah	W.2	34.1	429	1.5	1.8	24
Nevada	26.3	27.8	343	1.1	1.2	1.7
Pacific						
Washington	46.8	47.1	51.9	1.4	1.4	1.7
Oregon	51.5	50.9	57.5	1.7	1.8	23
California	327	320	328	1.5	1.5	13
Alaska	43.0	48.6	39.1	4.1	4.6	3.0
Hawaii	61.2	57.6	60.8	1.8	1.8	20
Median State	433	44.4	45.5	1.5	1.6	1.8
United States	45.8	46.4	475	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989. FSP participation counts are from Food Stamp Program Statistical Summary of Operations data, adjusted for errors in issuance.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.13

INDMDUAL POVERTY RATES BY STATE, 1988
ALTERNATIVE REGRESSION ESTIMATES
(Percent)

Division/ State	Poverty Rates		Standard Errors	
	Best Model	Next-Best Model	Best Model	Next-Best Model
New England				
Maine	13.1	1.20	0.4	0.9
New Hampshire	5.0	4.4	0.7	0.9
Vermont	12.4	11.1	03	0.9
Massachusetts	9.6	8.7	0.6	0.9
Rhode Island	11%	10.2	03	0.8
Connecticut	4.2	5.4	0.8	0.8
Middle Atlantic				
New York	11.8	12.1	05	0.6
New Jersey	6.5	75	0.7	0.7
Pennsylvania	10.6	11.7	05	03
East North Central				
Ohio	11.0	11.3	0.3	03
Indiana	10.2	10.5	0.4	0.4
Illinois	10.3	10.5	0.3	0.4
Michigan	11.4	11.1	0.4	0.3
Wisconsin	12.3	12.9	03	03
West North Central				
Minnesota	8.6	9.1	0.4	0.4
Iowa	10.8	11.1	0.4	0.4
Missouri	123	12.5	03	03
North Dakota	11.6	122	0.6	0.5
South Dakota	12.1	129	0.5	0.5
Nebraska	93	10.2	0.4	0.4
Kansas	9.4	9.6	0.4	0.4
South Atlantic				
Delaware	9.4	9.8	03	0.4
Maryland	81	8.5	0.4	0.5
District of Columbia	14.1	13.2	LO	02
Virginia	10.0	10.8	0.4	0.4
west Virginia	16.8	17.8	0.6	OS
North Carolina	15.4	15.5	03	a4
South Carolina	17.7	17.4	0.5	0.4
Georgia	16.1	15.7	0.4	0.4
Florida	13.4	11.9	0.8	03

TABLE V.13 (continued)

Division/ State	Poverty Rates		Standard Errors	
	Best Model	Next-Best Model	Best Model	Next-Best Model
East South Central				
Kentucky	17.9	18.7	0.6	0.5
Tennessee	173	17.6	0.5	0.5
Alabama	20.0	20.2	0.6	0.6
Mississippi	25.0	25.5	1.0	0.9
West South Central				
Arkansas	20.0	20.2	0.6	0.6
Louisiana	23.2	23.1	0.8	0.9
Oklahoma	18.2	18.2	0.7	0.7
Texas	175	16.5	0.8	0.7
Mountain				
Montana	11.9	11.9	05	0.5
Idaho	11.2	113	0.5	0.5
Wyoming	12.6	13.2	0.8	0.8
Colorado	13.2	13.2	0.7	0.7
New Mexico	19.6	19.0	0.8	0.7
Arizona	11.9	10.8	0.7	0.4
Utah	11.1	103	0.7	0.6
Nevada	8.6	8.4	0.5	0.4
Pacific				
Washington	11.1	10.4	0 5	0.3
Oregon	11.4	10.5	0.6	0.4
California	14.8	14.9	0.6	0.6
Alaska	9.9	10.9	0.9	0.8
Hawaii	10.3	10.1	0.4	0.3
Median State	11.8	11.7	0.5	0.5
United States	13.0	13.0	[a]	[a]

SOURCE: Poverty counts and FSP eligibility counts arc from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.14

INDIVIDUAL POVERTY RATES BY STATE, 1986-1988
SHRINKAGE ESTIMATES
(Percent)

Division/ State	Poverty Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	113	11.4	12.9	L1	1.2	1.0
New Hampshire	4.2	3.6	5.6	0.9	0.9	0.9
Vermont	11.0	99	11.1	L1	1.2	0.9
Massachusetts	8.1	8.0	8.8	0.9	03	0.7
Rhode Island	9.4	8.8	11.2	LO	1.1	09
Connecticut	63	6.5	4.2	0.9	1.0	09
Middle Atlantic						
New York	12.9	14.0	12.7	0.7	0.7	0.7
New Jersey	8.4	8.6	63	0.8	0.9	0.6
Pennsylvania	11.2	11.0	10.4	0.7	0.8	0.7
East North Central						
Ohio	128	13.2	11.8	0.8	0.9	0.7
Indiana	12.6	11.7	10.2	0.9	1.0	0.9
Illinois	123	13.0	11.5	0.8	0.9	0.7
Michigan	13.0	121	11.8	0.8	0.9	0.7
Wisconsin	128	10.8	10.7	0.9	1.0	0.9
West North Central						
Minnesota	11.2	10.7	9.4	0.9	1.1	0.9
Iowa	12.8	13.1	10.4	0.9	1.1	0.9
Missouri	13.9	13.6	12.3	0.9	1.0	0.9
North Dakota	13.6	126	115	1.0	1.1	1.0
South Dakota	15.2	14.5	12.6	1.0	1.1	1.0
Nebraska	126	11.8	10.0	1.0	1.1	1.0
Kansas	113	10.5	9.1	0.9	1.1	02
South Atlantic						
Delaware	11.6	9.4	9.1	0.9	1.0	0.9
Maryland	9.5	9.5	8.6	0.9	1.0	02
District of Columbia	122	133	14.2	1.1	13	L2
Virginia	11.2	10.7	10.2	0.9	1.0	0.9
West Virginia	19.5	19.4	16.6	1.0	1.2	1.1
North Carolina	15.9	153	13.8	0.9	1.0	0.7
South Carolina	18.4	173	16.9	1.0	1.1	1.0
Georgia	15.8	15.7	15.4	0.9	1.0	1.0
Florida	11.6	128	13.6	0.4	0.4	0.7

TABLE V.14 (continued)

Division/ State	Poverty Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	18.8	183	17.4	1.0	1.2	1.1
Tennessee	183	17.8	17.1	1.0	1.1	1.0
Alabama	21.1	20.5	19.4	1.1	1.2	1.1
Mississippi	25.1	25.0	24.6	13	1.4	1.4
West South Central						
Arkansas	20.6	20.8	19.8	1.1	1.2	1.1
Louisiana	22.3	23.2	22.8	1.1	13	1.2
Oklahoma	17.5	17.8	17.9	1.1	1.2	1.1
Texas	17.1	16.8	17.8	0.8	0.9	0.9
Mountain						
Montana	14.7	14.7	12.5	1.0	1.2	1.0
Idaho	15.3	13.4	11.5	1.0	1.2	1.0
Wyoming	14.7	12.9	12.0	1.1	1.2	1.1
Colorado	13.6	13.1	13.2	1.0	1.2	1.1
New Mexico	19.9	19.2	20.2	1.1	13	1.1
Arizona	13.1	12.1	125	0.9	1.1	1.0
Utah	13.5	11.6	10.8	1.0	1.1	1.0
Nevada	9.6	10.1	8.7	0.9	1.1	0.9
Pacific						
Washington	11.8	11.4	10.5	0.9	1.1	0.9
Oregon	127	123	11.3	0.9	1.1	1.0
California	13.0	13.0	13.8	0.6	0.6	0.7
Alaska	10.3	11.0	103	1.0	1.1	1.1
Hawaii	11.4	10.2	10.5	0.9	1.0	0.9
Median State	128	128	11.8	0.9	1.1	0.9
United States	13.6	13.5	13.0	a	a	a

SOURCE Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable Thus, we do not report standard errors for any national estimates.

TABLE V.15

INDIVIDUAL FSP ELIGIBILITY RATES BY STATE, 1986-1988
SHRINKAGE ESTIMATES
(Percent)

Division/ State	FSP Eligibility Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	14.2	13.9	14.4	1.3	1.4	L4
New Hampshire	5.3	5.5	6.9	1.0	1.1	1.3
Vermont	13.3	11.6	12.0	1.3	13	1.3
Massachusetts	10.5	9.8	10.7	LO	1.0	0.8
Rhode Island	12.0	10.9	11.9	13	13	1.3
Connecticut	8.1	7.6	6.0	1.1	1.2	1.1
Middle Atlantic						
New York	15.8	16.4	15.5	0.8	0.8	0.8
New Jersey	10.3	9.5	7.9	0.9	0.9	0.7
Pennsylvania	13.0	13.3	13.5	0.8	0.9	0.8
East North Central						
Ohio	15.1	15.0	14.7	0.9	0.9	0.8
Indiana	15.2	14.1	12.0	1.1	1.1	1.2
Illinois	15.3	15.2	13.7	0.9	0.9	0.9
Michigan	14.8	13.9	12.6	0.9	1.0	0.8
Wisconsin	14.8	13.0	11.6	1.1	1.1	1.1
West North Central						
Minnesota	13.1	124	11.4	1.1	1.2	1.2
Iowa	15.2	15.0	12.6	1.2	1.2	13
Missouri	16.1	15.5	14.4	1.1	1.1	1.2
North Dakota	15.2	13.8	13.0	1.2	1.2	1.1
South Dakota	18.0	17.9	14.8	1.2	13	1.2
Nebraska	1s.S	13.6	12.6	1.2	13	13
Kansas	13.6	12.8	11.8	1.2	1.2	1.2
South Atlantic						
Delaware	14.4	11.8	11.4	1.2	1.2	1.2
Maryland	123	10.6	10.1	1.1	1.1	1.2
District of Columbia	15.7	15.6	15.1	1.4	1.5	1.4
Virginia	13.3	12.9	127	1.1	1.2	1.1
West Virginia	24.3	23.5	20.8	13	1.4	13
North Carolina	195	18.5	16.9	1.1	1.2	0.9
south Carolina	220	21.1	19.8	1.2	1.3	13
Georgia	19.9	18.9	17.9	1.1	1.2	1.2
Florida	14.3	15.8	15.0	0.5	0.5	0.8

TABLE V.15 (continued)

Division/ State	FSP Eligibility Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	23.1	224	220	13	1.4	1.4
Tennessee	22.5	216	21.1	1.2	1.3	13
Alabama	26.0	253	24.1	1.3	1.4	1.4
Mississippi	31.6	30.6	29.9	1.5	1.6	1.6
West South Central						
Arkansas	25.3	24.9	23.8	13	1.4	1.4
Louisiana	27.2	26.6	273	1.4	1.4	1.5
Oklahoma	21.1	21.7	21.8	13	1.4	1.4
Texas	21.0	20.0	19.8	0.9	1.0	03
Mountain						
Montana	167	17.1	14.9	1.2	13	13
Idaho	17.5	16.5	14.6	13	13	13
Wyoming	17.0	14.2	14.1	1.4	1.4	1.4
Colorado	16.5	14.8	15.6	13	13	1.4
New Mexico	233	22.7	24.0	13	1.4	1.4
Arizona	15.9	14.9	135	1.2	1.2	1.2
Utah	15.4	14.7	13.1	1.2	13	13
Nevada	11.1	128	10.6	1.1	13	1.2
Pacific						
Washington	14.6	13.0	113	1.2	1.2	1.1
Oregon	14.8	14.6	13.2	1.2	1.3	13
California	15.5	15.0	15.4	0.6	0.7	0.8
Alaska	14.5	13.8	13.7	1.3	1.3	1.4
Hawaii	14.3	127	128	1.2	1.2	1.2
Median State	15.3	14.8	13.7	1.2	1.2	1.2
United States	16.6	15.9	15.1	[a]	[a]	[a]

SOURCE Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.16

NUMBER OF INDIVIDUALS IN POVERTY BY STATE, 1986-1988
SHRINKAGE ESTIMATES
(Thousands of Individuals)

Division/ State	Individuals In Poverty 1986	1987	1988	standard Errors 1986	1987	1988
New England						
Maine	127	131	155	12	14	12
New Hampshire	42	38	61	9	9	10
Vermont	58	53	59	6	6	5
Massachusetts	475	465	518	53	52	41
Rhode Island	89	86	113	10	11	9
Connecticut	1%	206	135	28	31	29
Middle Atlantic						
New York	2,260	2,460	2,231	123	123	123
New Jersey	643	646	482	61	68	46
Pennsylvania	1,323	1,301	1,254	82	94	85
East North Central						
Ohio	1,367	1,410	1,284	86	96	76
Indiana	670	636	562	48	55	SO
Illinois	1,411	1,496	1,310	92	104	79
Michigan	1,183	1,082	1,084	73	80	65
Wisconsin	601	509	502	42	47	42
West North Central						
Minnesota	461	462	416	37	47	40
Iowa	371	381	292	26	32	25
Missouri	695	693	642	45	51	47
North Dakota	88	82	75	7	7	7
South Dakota	106	103	89	7	8	7
Nebraska	203	192	160	16	18	16
Kansas	273	254	217	22	27	22
South Atlantic						
Delaware	74	60	60	6	6	6
Maryland	428	428	401	41	45	42
District of Columbia	74	76	82	7	7	7
Virginia	631	623	607	51	58	54
west Virginia	375	370	313	19	23	21
North Carolina	981	949	868	56	62	44
south Carolina	606	573	576	33	36	34
Georgia	953	948	958	54	60	62
Florida	1,370	1,575	1,693	47	49	87

TABLE V.16 (continued)

Division/ State	Individuals In Poverty			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	670	669	627	36	44	40
Tennessee	852	846	839	47	52	49
Alabama	848	820	780	44	48	44
Mississippi	656	639	636	34	36	36
West South Central						
Arkansas	482	501	484	26	29	27
Louisiana	966	1,003	968	48	56	51
Oklahoma	558	567	564	35	38	35
Texas	2793	2,748	2,968	131	147	150
Mountain						
Montana	121	117	99	8	10	8
Idaho	149	133	114	10	12	10
Wyoming	73	59	55	5	5	5
Colorado	431	422	426	32	39	36
New Mexico	286	283	302	16	19	16
Arizona	443	418	436	30	38	35
Utah	223	192	179	17	18	17
Nevada	97	103	95	9	11	10
Pacific						
Washington	518	512	483	39	49	42
Oregon	344	334	308	24	30	27
California	3,512	3,617	3,841	162	167	195
Alaska	53	56	49	5	6	5
Hawaii	116	110	111	9	11	9
Median State	461	462	436	33	38	35
United States	32,327	32,441	31,566	[a]	[a]	[a]

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.17

NUMBER OF INDIVIDUALS ELIGIBLE FOR THE FSP BY STATE, 1986-1988
SHRINKAGE ESTIMATES
(Thousands of Individuals)

Division/ State	individuals Eligible for the FSP			Standard Errors		
	1986	1987	1988	1986	1987	1988
New England						
Maine	160	160	173	15	16	17
New Hampshire	53	58	75	10	12	14
Vermont	70	62	64	7	7	7
Massachusetts	614	572	627	58	58	47
Rhode Island	114	107	120	12	13	13
Connecticut	253	239	192	34	38	35
Middle Atlantic						
New York	2,778	2,888	2,733	141	141	141
New Jersey	785	717	603	69	68	53
Pennsylvania	1,532	1,570	1,636	94	106	97
East North Central						
Ohio	1,616	1,606	1,603	%	96	87
Indiana	807	768	664	58	60	66
Illinois	1,751	1,754	1,554	103	104	102
Michigan	1,349	1,241	1,162	82	89	74
Wisconsin	695	615	545	52	52	52
West North Central						
Minnesota	541	534	504	45	52	53
Iowa	442	436	355	35	35	34
Missouri	805	790	749	55	56	62
North Dakota	99	90	85	8	8	7
South Dakota	125	127	105	8	9	8
Nebraska	251	221	202	19	19	21
Kansas	331	311	283	29	29	29
South Atlantic						
Delaware	92	75	75	8	8	8
Maryland	554	480	470	50	so	56
District of Columbia	95	89	87	8	9	8
Virginia	748	749	758	62	70	66
West Virginia	468	449	391	25	27	24
North Carolina	1,205	1,149	1,067	68	7s	57
South Carolina	723	6%	674	39	43	44
Georgia	1,199	1,138	1,115	66	72	75
Florida	1,684	1,936	1,875	59	61	100

TABLE V.17 (continued)

Division/ State	Individuals Eligible for the FSP			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	822	818	793	46	51	50
Tennessee	1,046	1,025	1,034	56	62	64
Alabama	1,047	1,012	968	52	56	56
Mississippi	825	781	774	39	41	41
West South Central						
Arkansas	593	600	582	30	34	34
Louisiana	1,180	1,150	1,160	61	61	64
Oklahoma	672	694	686	41	45	44
Texas	3,438	3,266	3,304	147	163	150
Mountain						
Montana	137	137	118	10	10	10
Idaho	170	164	145	13	13	13
Wyoming	84	65	64	7	6	6
Colorado	521	47s	505	41	42	45
New Mexico	334	335	359	19	21	21
Arizona	538	514	471	41	41	42
Utah	256	244	218	20	22	22
Nevada	112	131	115	11	13	13
Pacific						
Washington	638	584	523	52	54	51
Oregon	400	397	360	32	35	35
California	4,198	4,177	4,290	162	195	223
Alaska	75	71	66	7	7	7
Hawaii	146	137	135	12	13	13
Median State	554	534	505	41	42	44
United States	39,172	38,402	37,212	[a]	[a]	[a]

SOURCE: Poverty counts and FSP eligibility counts arc from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.18

ADJUSTED INDIVIDUAL FSP PARTICIPATION RATES BY STATE, 19861988
SHRINKAGE ESTIMATES
(Percent)

Division/ State	Adjusted FSP Participation Rates 1986	1987	1988	Standard Errors 1986	1987	1988
New England						
Maine	65.5	56.8	46.8	6.0	5.7	4.6
New Hampshire	40.2	31.4	24.7	7.6	6.3	4.7
Vermont	49.2	53.2	50.2	4.8	6.0	5.4
Massachusetts	49.4	50.9	48.0	4.7	5.2	3.6
Rhode Island	53.7	54.1	45.7	5.8	6.5	5.0
Connecticut	48.1	46.1	56.0	6.5	73	103
Middle Atlantic						
New York	58.0	54.7	53.5	3.0	27	28
New Jersey	528	50.2	57.5	4.6	4.8	5.1
Pennsylvania	63.6	58.7	55.9	3.9	4.0	33
East North Central						
Ohio	66.0	65.4	643	4.0	3.9	35
Indiana	41.8	39.3	421	3.0	3.1	4.2
Illinois	60.1	58.0	63.9	3.5	3.4	4.2
Michigan	65.2	68.4	73.7	4.0	4.9	4.7
Wisconsin	49.1	52.2	53.7	3.7	4.4	5.1
West North Central						
Minnesota	41.3	424	46.6	3.5	4.1	4.9
Iowa	45.2	42.6	46.1	3.6	3.4	4.4
Missouri	45.2	46.5	51.1	3.1	3.3	43
North Dakota	36.0	37.2	427	28	3.3	3.6
South Dakota	423	40.8	47.5	28	3.0	3.9
Nebraska	37.8	433	44.8	29	3.8	4.6
Kansas	34.4	37.8	41.1	3.0	3.5	4.2
South Atlantic						
Delaware	31.9	36.2	37.8	27	3.7	4.0
Maryland	46.0	49.7	47.6	4.1	5.2	5.7
District of Columbia	65.4	63.5	65.1	5.9	6.1	61
Virginia	43.6	41.0	42.5	3.6	3.8	3.7
west Virginia	55.0	56.0	63.0	3.0	33	4.0
North Carolina	35.0	33.7	35.4	20	22	1.9
South Carolina	41.0	37.5	36.9	23	23	24
Georgia	39.6	39.5	41.0	2.2	25	28
Florida	34.8	30.6	33.2	1.2	1.0	1.8

TABLE V.18 (continued)

Division/ State	Adjusted FSP Participation Rates			Standard Errors		
	1986	1987	1988	1986	1987	1988
East South Central						
Kentucky	62.3	56.3	57.9	3.5	3.5	3.7
Tennessee	46.2	45.9	46.2	25	28	29
Alabama	44.0	41.6	426	22	23	25
Mississippi	57.5	624	61.8	27	3.3	33
West South Central						
Arkansas	38.7	37.2	37.8	2.0	21	22
Louisiana	56.8	613	603	2.9	3.2	33
Oklahoma	37.8	38.5	373	23	25	24
Texas	38.3	435	43.9	1.7	22	2.0
Mountain						
Montana	41.1	415	45.4	3.0	3.2	4.0
Idaho	33.7	35.2	40.9	2.5	28	3.7
Wyoming	320	40.1	39.6	27	4.0	3.9
Colorado	343	40.0	39.8	27	3.5	3.6
New Mexico	44.5	43.8	37.9	2.5	27	22
Arizona	35.9	39.6	51.0	27	3.2	4.5
Utah	30.4	34.8	41.1	24	3.1	4.1
Nevada	29.8	25.2	32.3	3.0	26	3.7
Pacific						
Washington	44.7	49.1	56.8	3.7	4.5	5.5
Oregon	53.4	50.1	54.7	4.3	4.5	5.4
California	37.0	37.0	37.0	1.4	1.7	1.9
Alaska	34.8	41.0	37.4	3.2	3.9	3.9
Hawaii	60.5	59.7	57.3	5.1	5.7	5.4
Median State	44.0	433	46.1	3.0	3.4	3.9
United States	47.1	47.0	48.1	a	a	a

SOURCE Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989. FSP participation counts are from Food Stamp Porgram Statistical Summary of operations data, adjusted for errors in issuance.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.19

INDIVIDUAL POVERTY RATES BY STATE, 1988
ALTERNATIVE SHRINKAGE ESTIMATES
(Percent)

Division/ State	Poverty Rates		Standard Errors	
	Best Model	Next-Best Model	Best Model	Next-Best Model
New England				
Maine	12.9	12.3	1.0	1.2
New Hampshire	5.6	5.4	0.9	1.1
Vermont	11.1	10.0	0.9	1.1
Massachusetts	8.8	8.5	0.7	0.7
Rhode Island	112	10.0	0.9	1.1
Connecticut	4.2	4.7	0.9	0.9
Middle Atlantic				
New York	127	12.8	0.7	0.8
New Jersey	6.3	6.5	0.6	0.6
Pennsylvania	10.4	10.7	0.7	0.7
East North Central				
Ohio	11.8	120	0.7	0.7
Indiana	10.2	10.4	0.9	1.0
Illinois	11.5	11.7	0.7	0.8
Michigan	11.8	11.7	0.7	0.8
Wisconsin	10.7	10.8	0.9	0.9
West North Central				
Minnesota	9.4	9.9	0.9	1.0
Iowa	10.4	10.5	0.9	1.0
Missouri	12.3	12.5	0.9	1.0
North Dakota	115	12.0	1.0	1.0
South Dakota	126	13.3	1.0	1.0
Nebraska	10.0	10.2	1.0	1.1
Kansas	9.1	9.0	0.9	LO
South Atlantic				
Delaware	9.1	9.4	0.9	1.0
Maryland	8.6	8.9	0.9	1.0
District of Columbia	14.2	13.4	1.2	1.2
Virginia	10.2	10.8	0.9	1.0
west Virginia	16.6	17.6	1.1	1.1
North Carolina	13.8	13.6	0.7	0.8
South Carolina	16.9	16.7	1.0	1.1
Georgia	15.4	15.0	1.0	1.0
Florida	13.6	13.0	0.7	0.7

TABLE V.19 (continued)

Division/ State	Poverty Rates		Standard Errors	
	Best Model	Next-Best Model	Best Model	Next-Best Made1
East South Central				
Kentucky	17.4	18.2	1.1	1.1
Tennessee	17.1	175	1.0	1.1
Alabama	19.4	19.7	1.1	12
Mississippi	24.6	25.4	1.4	1.4
West South Central				
Arkansas	19.8	20.3	1.1	1.2
Louisiana	22.8	22.9	1.2	1.3
Oklahoma	17.9	18.0	1.1	1.2
Texas	17.8	17.4	0.9	0.9
Mountain				
Montana	12.5	127	1.0	1.1
Idaho	11.5	11.7	1.0	1.1
Wyoming	120	123	1.1	1.2
Colorado	13.2	13.2	1.1	1.2
New Mexico	20.2	20.0	1.1	1.2
Arizona	125	11.7	1.0	1.1
Utah	10.8	10.2	1.0	1.1
Nevada	8 7	8.4	0.9	1.0
Pacific				
Washington	10.5	9.7	0.9	1.0
Oregon	113	10.5	1.0	1.1
California	13.8	13.7	0.7	0.8
Alaska	10.3	11.0	1.1	13
Hawaii	10.5	10.4	0.9	1.0
Median State	11.8	11.7	0.9	1.0
United States	13.0	13.0	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United Stats totals implied by the regression and shrinkage estimates for States arc not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.20

INDIVIDUAL FSP ELIGIBILITY RATES BY STATE, 1988
ALTERNATIVE SHRINKAGE ESTIMATES
(Percent)

Division/ State	FSP Eligibility Rates: Estimated standard Errors used	FSP Eligibility Rates: Inflated standard Errors Used	standard Errors: Estimated Standard Errors Used	standard Errors: Inflated Standard Errors Used
New England				
Maine	14.4	14.4	1.4	1.3
New Hampshire	6.9	6.5	13	13
Vermont	12.0	126	13	13
Massachusetts	10.7	10.6	0.8	0.9
Rhode Island	11.9	121	13	13
Connecticut	6.0	6.1	1.1	1.1
Middle Atlantic				
New York	15.5	15.1	0.8	0.9
New Jersey	7.9	8.1	0.7	0.8
Pennsylvania	13.5	13.6	0.8	0.8
East North Central				
Ohio	14.7	143	0.8	0.9
Indiana	12.0	12.3	1.2	1.1
Illinois	13.7	13.3	09	0.9
Michigan	12.6	12.8	0.8	0.8
Wisconsin	11.6	13.0	1.1	1.0
West North Central				
Minnesota	11.4	11.2	1.2	1.1
Iowa	12.6	129	1.2	1.1
Missouri	14.4	14.5	1.2	1.1
North Dakota	13.0	13.7	1.1	1.1
South Dakota	14.8	15.0	1.2	1.1
Nebraska	12.6	124	13	1.2
Kansas	11.8	11.6	1.2	1.1
South Atlantic				
Delaware	11.4	11.5	1.2	1.1
Maryland	10.1	10.1	l.2	1.1
District of Columbia	15.1	15.0	1.4	13
Virginia	12.7	12.7	L1	1.1
west Virginia	20.8	20.7	1.3	L2
North Carolina	16.9	17.2	0.9	0.9
South Carolina	19.8	20.0	13	1.2
Georgia	17.9	18.0	1.2	1.1
Florida	15.0	14.7	0.8	0.8

TABLE V.20 (continued)

Division/ State	FSP Eligibility Rates: Estimated Standard Errors used	FSP Eligibility Rates: Inflated Standard Errors used	Standard Errors: Estimated Standard Errors used	Standard Errors: Inflated Standard Errors Used
East South Central				
Kentucky	22.0	21.8	1.4	13
Tennessee	21.1	20.7	13	13
Alabama	24.1	23.6	1.4	13
Mississippi	29.9	29.4	1.6	1.6
West South Central				
Arkansas	23.8	23.5	1.4	13
Louisiana	273	27.1	1.5	1.5
Oklahoma	21.8	21.6	1.4	1.4
Texas	19.8	19.7	0.9	1.0
Mountain				
Montana	14.9	14.6	1.3	1.2
Idaho	14.6	14.1	13	1.2
Wyoming	14.1	15.0	1.4	1.4
Colorado	15.6	15.8	1.4	13
New Mexico	24.0	233	1.4	1.4
Arizona	13.5	13.2	1.2	1.1
Utah	13.1	12.9	13	1.2
Nevada	10.6	103	13	1.1
Pacific				
Washington	113	11.7	1.1	1.1
Oregon	13.2	12.9	13	1.2
California	15.4	15.8	0.8	0.9
Alaska	13.7	13.5	1.4	1.4
Hawaii	128	12.4	1.2	1.1
Median State	13.7	13.7	1.2	1.1
United States	15.1	15.1	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.21

INDIVIDUAL POVERTY **RATES** BY STATE, 1988
ALTERNATIVE ESTIMATION METHODS
(Percent)

Division/ State	Poverty Rates			Standard Errors		
	Sample Estimates	Regression Estimates	Shrinkage Estimates	Sample Estimates	Regression Estimates	Shrinkage Estimates
New England						
Maine	**13.2**	13.1	**12.9**	1.9	0.4	LO
New Hampshire	**6.7**	5.0	**5.6**	1.5	0.7	03
Vermont	81	**12.4**	**11.1**	**1.7**	03	03
Massachusetts	8.5	9.6	**8.8**	**0.8**	0.6	0.7
Rhode Island	9.8	11.8	**11.2**	1.8	03	03
Connecticut	4.0	4.2	**4.2**	**1.2**	0.8	0.9
Middle Atlantic						
New York	13.4	11.8	**12.7**	0.9	0.5	0.7
New Jersey	6.2	**6.5**	6.3	0.7	0.7	0.6
Pennsylvania	10.3	10.6	10.4	0.8	**0.5**	0.7
East North Central						
Ohio	12.4	11.0	11.8	0.9	0.3	0.7
Indiana	10.1	10.2	10.2	1.7	0.4	0.9
Illinois	12.7	10.3	11.5	1.0	0.3	0.7
Michigan	121	11.4	11.8	0.9	0.4	0.7
Wisconsin	7.8	12.3	10.7	1.5	0.3	0.9
West North Central						
Minnesota	11.6	8.6	9.4	1.8	0.4	**0.9**
Iowa	9.4	10.8	10.4	1.6	0.4	**0.9**
Missouri	127	123	**12.3**	1.9	0.3	0.9
North Dakota	11.6	11.6	**11.5**	1.6	0.6	1.0
South Dakota	14.2	**12.1**	**12.6**	1.7	0.5	LO
Nebraska	103	9.9	10.0	2.1	0.4	LO
Kansas	81	9.4	9.1	1.5	0.4	03
South Atlantic						
Delaware	**8.6**	9.4	9.1	1.6	03	03
Maryland	9.8	8.1	8.6	1.7	0.4	0.9
District of Columbia	15.2	14.1	14.2	21	1.0	**1.2**
Virginia	10.8	10.0	10.2	1.5	0.4	0.9
west Virginia	17.9	16.8	16.6	2.2	0.6	1.1
North Carolina	126	15.4	13.8	0.9	0.3	0.7
South Carolina	15.5	17.7	16.9	1.8	0.5	1.0
Georgia	14.0	16.1	15.4	1.8	0.4	1.0
Florida	13.6	13.4	13.6	0.9	0.8	0.7

TABLE V.21 (continued)

Division/ State	Poverty Rates			Standard Errors		
	Sample Estimates	Regression Estimates	Shrinkage Estimates	Sample Estimates	Regression Estimates	Shrinkage Estimates
East South Central						
Kentucky	17.6	17.9	17.4	22	0.6	1.1
Tennessee	18.0	173	17.1	2.1	0.5	1.0
Alabama	193	20.0	19.4	23	0.6	1.1
Mississippi	27.2	25.0	24.6	2.4	LO	1.4
West South Central						
Arkansas	21.6	20.0	19.8	2.2	0.6	1.1
Louisiana	22.8	23.2	22.8	24	0.8	13
Oklahoma	173	18.2	17.9	21	0.7	1.1
Texas	18.0	175	17.8	1.1	0.8	0.9
Mountain						
Montana	14.6	11.9	12.5	1.9	0.5	1.0
Idaho	125	11.2	115	1.8	0.5	1.0
Wyoming	9.6	12.6	120	1.9	0.8	1.1
Colorado	125	13.2	13.2	1.9	0.7	1.1
New Mexico	23.0	19.6	20.2	2.1	0.8	1.1
Arizona	14.1	11.9	12.5	1.9	0.7	1.0
Utah	9.8	11.1	10.8	1.6	0.7	1.0
Nevada	8.6	8.6	8.7	1.7	0.5	0.9
Pacific						
Washington	8.7	11.1	10.5	1.6	0.5	0.9
Oregon	10.4	11.4	11.3	1.9	0.6	1.0
California	13.2	14.8	13.8	0.9	0.6	0.7
Alaska	11.0	9.9	103	1.7	0.9	1.1
Hawaii	11.1	103	105	1.8	0.4	0.9
Median State	12.4	11.8	11.8	1.7	0 5	0.9
United States	13.0	13.0	13.0	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.22

INDIVIDUAL FSP ELIGIBILITY RATES BY STATE, 1988
ALTERNATIVE ESTIMATION METHODS
(Percent)

Division/ State	FSP Eligibility Rates			Standard Errors		
	Sample Estimates	Regression Estimates	Shrinkage Estimates	Sample Estimates	Regression Estimates	Shrinkage Estimates
New England						
Maine	14.5	143	14.4	1.9	1.0	L4
New Hampshire	83	5.4	63	1.7	1.1	1.3
Vermont	10.1	13.2	12.0	1.8	LO	1.3
Massachusetts	10.9	10.2	10.7	0.9	1.1	0.8
Rhode Island	11.4	12.1	11.9	1.9	1.0	13
Connecticut	5.6	63	6.0	1.4	0.9	1.1
Middle Atlantic						
New York	16.2	14.1	15.5	1.0	0.6	0.8
New Jersey	7.7	8.7	7.9	0.8	0.8	0.7
Pennsylvania	13.4	13.9	13.5	1.0	0.4	0.8
East North Central						
Ohio	15.4	13.5	14.7	1.0	0.4	0.8
Indiana	11.3	12.6	12.0	1.8	0.5	1.2
Illinois	14.3	124	13.7	1.0	0.4	0.9
Michigan	12.4	13.3	12.6	1.0	0.4	0.8
Wisconsin	8.1	15.4	11.6	1.5	0.4	1.1
West North Central						
Minnesota	12.1	10.9	11.4	1.8	0.5	12
Iowa	11.6	13.4	126	1.7	0.5	1.2
Missouri	13.9	14.9	14.4	1.9	0.4	12
North Dakota	11.2	14.7	13.0	1.6	0.6	1.1
South Dakota	14.2	15.5	14.8	1.7	0.5	1.2
Nebraska	13.7	123	12.6	24	0.5	L3
Kansas	12.2	115	11.8	1.8	0.5	L2
South Atlantic						
Delaware	11.1	11.7	11.4	1.8	0.4	1.2
Maryland	10.1	10.1	10.1	1.7	0.6	1.2
District of Columbia	15.2	15.3	15.1	21	1.0	1.4
Virginia	12.7	12.8	127	1.6	0.4	1.1
West Virginia	21.0	21.2	20.8	23	0.6	13
North Carolina	16.3	18.4	16.9	1.1	0.4	0.9
South Carolina	19.0	20.7	19.8	20	0.5	13
Georgia	17.3	18.6	17.9	1.9	0.5	1.2
Florida	15.4	14.1	15.0	0.9	0.4	0.8

TABLE V.22 (continued)

Division/ State	FSP Eligibility Rates Sample Estimates	Regression Estimates	Shrinkage Estimates	Standard Errors Sample Estimates	Regression Estimates	Shrinkage Estimates
East South Central						
Kentucky	22.9	221	22.0	'24	0.6	1.4
Tennessee	224	202	21.0	2.2	0.5	1.3
Alabama	25.9	23.9	24.1	2.5	0.7	1.4
Mississippi	31.0	30.1	29.9	2.5	1.1	1.6
West South central						
Arkansas	24.7	23.9	23.8	2.3	0.7	1.4
Louisiana	27.8	27.5	273	2.5	1.0	1.5
Oklahoma	22.1	21.8	21.8	2.3	0.8	1.4
Texas	19.8	19.9	19.8	1.1	0.8	0.9
Mountain						
Montana	16.1	14.4	14.9	2.0	0.6	1.3
Idaho	16.5	13.6	14.6	20	0.6	1.3
Wyoming	10.7	16.1	14.1	20	0.9	1.4
Colorado	15.0	16.0	15.6	21	0.9	1.4
New Mexico	27.1	229	24.0	23	0.9	1.4
Arizona	14.8	12.9	13.5	20	0.4	1.2
Utah	14.1	126	13.1	1.9	0.7	1.3
Nevada	11.5	10.0	10.6	1.9	0.5	1.2
Pacific						
Washington	10.1	12.4	113	1.7	0.4	1.1
Oregon	14.6	X2.6	13.2	22	0.5	1.3
California	14.7	17.4	15.4	1.0	0.7	0.8
Alaska	14.7	13.1	13.7	20	1.0	1.4
Hawaii	14.2	121	128	20	0.4	1.2
Median State	143	13.9	13.7	1.9	0.6	1.2
United States	15.3	15.5	15.1	a	a	a

SOURCE Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not dire&y obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.23

NUMBER OF INDIVIDUALS IN POVERTY BY STATE, 1988
ALTERNATIVE ESTIMATION METHODS
(Thousands of Individuals)

Division/ State	Individuals in Poverty			Standard Errors		
	Sample Estimates	Regression Estimates	Shrinkage Estimates	Sample Estimates	Regression Estimates	Shrinkage Estimates
New England						
Maine	159	157	155	22	5	12
New Hampshire	73	54	61	16	8	10
Vermont	43	66	59	9	2	5
Massachusetts	497	562	518	48	35	41
Rhode Island	99	119	113	18	3	9
Connecticut	128	136	135	39	26	29
Middle Atlantic						
New York	2,369	2,084	2,231	163	88	123
New Jersey	475	4%	482	52	53	46
Pennsylvania	1,246	1,287	1,254	103	61	85
East North Central						
Ohio	1,356	1,202	1,284	101	33	76
Indiana	560	562	562	95	22	50
Illinois	1,436	1,173	1,310	111	34	79
Michigan	1,112	1,051	1,084	87	37	65
Wisconsin	364	579	502	68	14	42
West North Central						
Minnesota	514	382	416	79	18	40
Iowa	263	304	292	45	11	25
Missouri	662	641	642	97	16	47
North Dakota	76	76	75	11	4	7
South Dakota	101	85	89	12	4	7
Nebraska	164	158	160	34	6	16
Kansas	195	226	217	35	10	22
South Atlantic						
Delaware	57	62	60	11	2	6
Maryland	457	379	401	80	19	42
District of Columbia	88	82	82	12	6	7
Virginia	647	5%	607	92	24	54
West Virginia	337	316	313	41	11	21
North Carolina	7%	970	868	60	19	44
South Carolina	528	603	576	62	17	34
Georgia	875	1,001	958	112	25	62
Florida	1,704	1,670	1,693	112	100	87

TABLE V.23 (continued)

Division/ State	Individuals in Poverty: Sample Estimates	Individuals in Poverty: Regression Estimates	Individuals in Poverty: Shrinkage Estimates	Standard Errors: Sample Estimates	Standard Errors: Regression Estimates	Standard Errors: Shrinkage Estimates
East South Central						
Kentucky	634	644	627	78	22	40
Tennessee	883	849	839	102	25	49
Alabama	775	804	780	91	24	44
Mississippi	704	647	636	62	26	36
West South Central						
Arkansas	527	488	484	55	15	27
Louisiana	968	984	968	101	34	51
Oklahoma	543	572	564	65	22	35
Texas	3,006	2,920	2,968	176	133	150
Mountain						
Montana	116	95	99	15	4	8
Idaho	124	111	114	18	5	10
Wyoming	43	57	55	8	4	5
Colorado	405	426	426	62	23	36
New Mexico	343	294	302	32	12	16
Arizona	491	415	436	67	24	35
Utah	162	184	179	27	12	17
Nevada	93	94	95	18	5	10
Pacific						
Washington	402	514	483	73	23	42
Oregon	285	312	308	51	16	27
caiifomia	3,687	4,111	3,841	259	167	195
Alaska	53	47	49	8	4	5
Hawaii	117	108	111	19	4	9
Median State	457	426	436	56	18	35
united States	31,745	31,751	31,566	a	a	a

SOURCE: Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totais implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.24

NUMBER OF INDIVIDUALS ELIGIBLE FOR THE FSP BY STATE, 1988
ALTERNATIVE ESTIMATION METHODS
(Thousands of Individuals)

Division/ State	Individuals Eligible for the FSP: Sample Estimates	Regression Estimates	Shrinkage Estimates	Standard Errors: Sample Estimate5	Regression Estimates	Shrinkage Estimates
New England						
Maine	174	172	173	23	12	17
New Hampshire	91	58	75	18	12	14
Vermont	54	70	64	10	5	7
Massachusetts	636	598	627	53	64	47
Rhode Island	115	122	120	19	10	13
Connecticut	179	200	192	46	29	35
Middle Atlantic						
New York	2,863	2494	2,733	176	106	141
New Jersey	586	664	603	58	61	53
Pennsylvania	1,627	1,685	1,636	116	48	97
East North Central						
Ohio	1,675	1,470	1,603	110	44	87
Indiana	627	698	664	100	28	66
Illinois	1,620	1,411	1,554	117	45	102
Michigan	1,146	1,224	1,162	88	37	74
Wisconsin	382	722	545	70	19	52
West North Central						
Minnesota	535	484	504	80	22	53
Iowa	327	376	355	49	14	34
Missouri	723	775	749	101	21	62
North Dakota	73	%	85	11	4	7
South Dakota	101	109	105	12	4	8
Nebraska	219	1%	202	38	8	21
Kansas	293	276	283	42	12	29
South Atlantic						
Delaware	73	77	75	12	3	8
Maryland	469	469	470	81	28	56
District of Columbia	88	88	87	12	6	8
Virginia	757	764	758	98	24	66
West Virginia	394	398	391	44	11	24
North Carolina	1,027	1,160	1,067	67	25	57
South Carolina	646	705	674	67	17	44
Georgia	1,075	1,157	1,115	121	31	75
Florida	1,921	1,760	1,875	117	50	100

TABLE V.24 (continued)

Division/ State	Individuals Eligible for the FSP			Standard Errors		
	Sample Estimates	Regression Estimates	Shrinkage Estimates	Sample Estimates	Regression Estimates	Shrinkage Estimates
East South Central						
Kentucky	825	797	793	86	22	50
Tennessee	1,096	1,024	1,034	110	25	64
Alabama	1,042	960	968	101	28	56
Mississippi	802	779	774	65	28	41
West South Central						
Arkansas	603	585	582	57	17	34
Louisiana	1,181	1,169	1,160	108	42	64
Oklahoma	695	686	686	71	25	44
Texas	3,304	3,319	3,304	183	133	150
Mountain						
Montana	128	114	118	16	5	10
Idaho	164	13s	14s	20	6	13
Wyoming	49	73	64	9	4	6
Colorado	487	517	505	67	29	4s
New Mexico	405	342	359	34	13	21
Arizona	516	450	471	69	14	42
Utah	234	209	218	31	12	22
Nevada	125	108	11s	20	5	13
Pacific						
Washington	466	572	523	78	18	51
Oregon	398	343	360	59	14	35
California	4,097	4,841	4,290	271	195	223
Alaska	71	63	66	9	5	7
Hawaii	149	127	135	21	4	13
Median State	487	517	505	65	19	44
United States	37333	37,692	37,212	a	a	a

SOURCE Poverty counts and FSP eligibility counts are from March Current Population Surveys, 1987 to 1989.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

TABLE V.25

ADJUSTED INDIVIDUAL FSP PARTICIPATION RATES BY STATE, 1988
ALTERNATIVE ESTIMATION METHODS
(Percent)

Division/ State	Adjusted FSP Participation Rates: Sample Estimates	Adjusted FSP Participation Rates: Regression Estimates	Adjusted FSP Participation Rates: Shrinkage Estimates	Standard Errors: Sample Estimates	Standard Errors: Regression Estimates	Standard Errors: Shrinkage Estimates
New England						
Maine	46.5	47.2	46.8	6.2	33	4.6
New Hampshire	20.4	31.8	24.7	4.1	6.5	4.7
Vermont	593	45.6	50.2	10.8	35	5.4
Massachusetts	47.4	50.4	48.0	4.0	5.4	3.6
Rhode Island	47.6	44.9	45.7	7.9	3.7	5.0
Connecticut	60.1	53.8	56.0	15.3	7.7	103
Middle Atlantic						
New York	51.0	58.6	53.5	3.1	25	28
New Jersey	59.1	52.1	57.5	5.8	4.8	5.1
Pennsylvania	56.2	54.2	559	4.0	1.6	33
East North Central						
Ohio	61.5	70.1	643	4.1	21	3.5
Indiana	44.5	40.0	421	7.1	1.6	4.2
Illinois	613	70.3	63.9	4.4	23	4.2
Michigan	74.7	70.0	73.7	5.8	2.1	4.7
Wisconsin	76.5	40.5	53.7	14.0	1.1	5.1
West North Central						
Minnesota	44.0	48.6	46.6	6.6	2.2	4.9
Iowa	49.9	43.4	46.1	7.5	1.6	4.4
Missouri	529	49.3	51.1	7.4	1.3	4.3
North Dakota	49.4	37.6	427	7.1	15	3.6
South Dakota	49.4	45.5	47.5	5.8	15	3.9
Nebraska	41.2	46.0	44.8	7.2	1.9	4.6
Kansas	39.8	423	4L1	5.7	1.8	4.2
South Atlantic						
Delaware	38.9	36.9	37.8	63	1.3	4.0
Maryland	47.7	47.7	47.6	8.2	2.8	5.7
District of Columbia	64.5	64.4	65.1	9.1	4.2	6.1
Virginia	425	421	425	5.5	13	3.7
west Virginia	625	61.9	63.0	7.0	1.8	4.0
North Carolina	36.8	326	35.4	24	0.7	1.9
South Carolina	38.5	353	36.9	4.0	0.9	24
Georgia	425	39.5	41.0	4.8	1.1	28
Florida	324	35.4	33.2	20	1.0	1.8

TABLE V.25 (continued)

Division/ State	Adjusted FSP Participation Rates			Standard Errors		
	Sample Estimates	Regression Estimates	Shrinkage Estimates	Sample Estimates	Regression Estimates	Shrinkage Estimates
East South Central						
Kentucky	55.7	57.6	57.9	5.8	1.6	3.7
Tennessee	43.6	46.6	46.2	4.4	1.1	29
Alabama	39.6	43.0	426	3.8	1.3	2.5
Mississippi	59.6	61.4	61.8	4.8	23	33
West South Central						
Arkansas	36.5	37.6	37.8	3.5	1.1	22
Louisiana	59.3	59.9	603	5.4	22	33
Oklahoma	36.8	373	373	3.8	1.4	24
Texas	43.9	43.7	43.9	24	1.8	20
Mountain						
Montana	421	47.0	45.4	53	20	4.0
Idaho	36.1	43.9	40.9	4.4	1.9	3.7
Wyoming	520	34.8	39.6	9.5	20	3.9
Colorado	41.2	38.8	39.8	5.7	22	3.6
New Mexico	33.6	39.8	37.9	2.8	1.6	22
Arizona	46.6	53.4	51.0	6.2	1.7	4.5
Utah	38.2	429	41.1	5.1	2.4	4.1
Nevada	29.7	34.3	323	4.9	1.7	3.7
Pacific						
Washington	63.8	519	56.8	10.7	1.7	5.5
Oregon	49.5	57.5	54.7	73	23	5.4
California	38.8	328	37.0	26	1.3	1.9
Alaska	34.9	39.1	37.4	4.7	3.0	3.9
Hawaii	51.8	60.8	573	7.2	20	5.4
Median State	46.6	45.5	46.1	5.7	1.8	3.9
United States	48.0	475	48.1	a	a	a

SOURCE: Poverty counts and FSP eligibility counts arc from March Current Population Surveys, 1987 to 1989. FSP participation counts are from Food Stamp Porgram Statistical Summary of Operations data, adjusted for errors in issuance.

[a]Standard errors for the United States totals implied by the regression and shrinkage estimates for States are not directly obtainable. Thus, we do not report standard errors for any national estimates.

VI. SUMMARY AND RECOMMENDATIONS

In this study, we consider five small-area estimation methods that can be used to obtain estimates of State poverty counts, State FSP eligibility counts, and State FSP participation rates:

1. The direct sample estimation method
2. The regression method
3. The ratio-correlation technique
4. Shrinkage methods
5. Structure preserving estimation (SPREE)

After weighing the relative advantages and disadvantages of all five methods, we recommend three methods for empirical application and testing. We recommend against the empirical application and testing of the ratio-correlation technique and SPREE for two principal reasons. First, both methods are computationally burdensome, requiring that we process census microdata to obtain FSP eligibility estimates. Second, both methods assume that the relationships between poverty or FSP eligibility and various socioeconomic and demographic indicators are stable, that a model estimated using census data pertains for each year until data from the next census are available (about two years after the census is taken). For this study, we would have to use 1980 census data because the required 1990 census data are not available. However, we have no reason to believe that the relevant multivariate relationships have remained stable over time, in general, and over the 1980s, in particular.[1] With no evidence suggesting that either the ratio-correlation technique or SPREE strongly dominates the regression or shrinkage methods in terms of lower sampling variability, we believe that it is prudent to avoid the potential biases from assuming temporal stability.

[1] Although SPREE requires a weaker temporal stability assumption than the ratio-correlation technique, data limitations would likely prevent our exploiting in practice that theoretical advantage of SPREE.

Each of the three estimation methods recommended for empirical application and testing requires sample data Among the potential sources of sample data, the leading candidates are the CPS and SIPP. We recommend against using SIPP as a source of sample data for this study because (1) SIPP, which is not designed for State estimation, provides small State sample sizes and, therefore, supports much less precise sample estimates than the CPS and (2) SIPP uniquely identifies only 42 States, including the District of Columbia.

Using CPS data and administrative records data such as data from vital statistics records, we obtain direct sample estimates, regression estimates, and shrinkage estimates of State poverty counts, State FSP eligibility counts, and State FSP participation rates for 1986, 1987, and 1988. We also derive estimates of State poverty rates and State FSP eligibility rates. Our shrinkage estimator is a hierarchical Empirical Bayes estimator that optimally combines direct sample estimates and regression estimates.

In our empirical evaluation of the direct sample, regression, and shrinkage methods, we find that the three methods generally agree on aggregate characteristics pertaining to the distriiution of State estimates. For the distribution of State FSP participation rates, for instance, such aggregate characteristics include the median State participation rate, the national participation rate implied by the State estimates, the standard deviation or interquartile range of the State participation rates, and the distribution of the State participation rates across broadly defined categories. For example, about one-third of the States had FSP participation rates below 40 percent, about one-third of the States had FSP participation rates between 40 percent and 50 percent, and about one-third of the States had FSP participation rates of 50 percent or more in 1986, 1987, and 1988 according to all three estimation methods. The direct sample, regression, and shrinkage methods also generally agree on which areas of the country tend to have higher participation rates and which areas tend to have lower participation rates.

Despite this general agreement among the direct sample, regression, and shrinkage methods on aggregate features of the distribution of State estimates, we find that, for some States, the three alternative estimates for a given year differ substantially. For example, differences of four percentage points between direct sample and regression estimates of FSP participation rates are common. Some of the observed differences in point estimates, however, can be attributed largely to sampling variability. When we compare interval estimates, that is, confidence intervals, we find that the regression and shrinkage methods mainly reduce our uncertainty, providing narrower confidence intervals than the direct sample estimation method. For some States, the confidence intervals from the regression method and, to a much ksser degree, the shrinkage method include values that we would consider unlikely based even on the relatively wide confidence intervals from the direct sample estimation method. But, for most States, the regression and shrinkage methods imply confidence intervals that he entirely inside the confidence intervals implied by the direct sample estimation method.

Although each of the three estimation methods has relative strengths and weaknesses, we recommend our shrinkage estimates over our direct sample estimates and regression estimates. We recommend shrinkage estimates over direct sample estimates primarily because our shrinkage estimates are substantially more reliable for many States. Overall, we find that the shrinkage estimator is statistically more efficient than the direct sample estimator. We recommend shrinkage estimates over regression estimates for three reasons. First, for the nation as a whole and for States for which we obtain precise direct sample estimates, we find closer agreement between direct sample and shrinkage estimates than between direct sample and regression estimates. Differences between shrinkage and direct sampk point estimates arc much smaller than differences between regression and direct sample point estimates. Also, the overlap between confidence intervals implied by shrinkage and direct sampk estimates is greater than the overlap between confidence intervals implied by regression and direct sample estimates. Second, although the standard errors of regression estimates are much smaller than the standard errors of shrinkage estimates for some States, we believe that our estimated standard errors exaggerate the overall precision of the regression estimates. We find that the covariances between regression estimates for different States are relatively large. Thus, the risk of obtaining many large estimation errors is higher with the regression method than with the direct sample and shrinkage methods. The covariances between regression estimates for different States are sufficiently large that, despite relative@ small standard errors of regression estimates for individual States, the regression estimator cannot be judged statistically more efficient than the shrinkage estimator or the direct sample estimator. Third, we find that the shrinkage estimator is less sensitive to model specification than the regression estimator. We find that similar regression models can yield moderately to substantially different e&mates for some States. By combining the regression estimates with direct sample estimates, the shrinkage estimator dampens differences between estimates from competing models.

Our final recommendation is that further research be undertaken to extend the findings of this study. We recommend obtaining State poverty and, possibly, FSP eligibility and participation estimates for 1989 using not only CPS data and the methods used in this report but also 1990 census data and the direct sample estimation method. Although our empirical results suggest that the shrinkage estimates are probably better than the direct sample estimates or the regression estimates, we are unable to compare any of our estimates to the true values or, at least, to unbiased estimates subject to very little sampling variability. We are concerned by this because our regression and shrinkage estimators are biased. We would like to measure the precision of regression and shrinkage estimates using a criterion such as mean square error that takes into account both bias and sampling error. However, we cannot estimate mean square error matrixes unless estimates that can be regarded as the truth or very near the truth are available as a standard of comparison. Although census estimates are subject to sampling variability and nonsampling error, they would provide a standard of comparison and allow a more complete evaluation of alternative methods and estimates.

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APPENDIX A

DETERMINING FSP ELIGIBILITY STATUS IN THE CPS

We simulate FSP eligibility status for individuals in the CPS in four main steps. In the first step, we create a CPS extract of potentially eligiile households. In the second step, we estimate monthly income from reported annual income for each household in our CPS extract. In the third step, we impute household net income for a selected month (August). In the fourth step, we determine each household's FSP eligibility status for that month. Each individual member of an eligible household is determined to be eligible for the FSP. The remainder of this appendix describes these steps in greater detail. Additional details are provided by Trippe, Doyle, and Asher (1991). The March 1989 CPS, which collected &come data for 1988, is used as an example where appropriate.

STEP ONE: CREATING THE CPS EXTRACT

Group quarters households and noninterview households arc excluded from the full CPS analysis file to create an extract. A household with-total income greater than 250 percent of the calculated poverty guideline for the household is also excluded, unless a member of the household received food stamps, AFDC, SSI, or GA during the previous calendar year. The Federal poverty guidelines of all families in the household, except subfamilies, are summed to obtain the poverty guideline for the household.

STEP TWO: ESTIMATING MONTHLY INCOME FROM ANNUAL AMOUNTS

We estimate from reported annual amounts four different types of monthly income: earnings, unemployment compensation, noncash transfers and other nonasset income, and cash welfare and asset income. Monthly income amounts are estimated for individuals and summed to obtain household totals.

To estimate monthly earnings for an individual, we divide the reported number of weeks worked by 4.333 to get the number of months worked and the reported number of weeks unemployed by 4.333 to get the number of months unemployed Reported total annual earnings is divided by the number of months worked to obtain average monthly earnings. For each month of the year, every individual age 15 and over is assigned an employment status of "working," "unemployed," or "not in the labor force" based on two randomly drawn numbers. One random number between 1 and 12 determines the month in which a consecutive string of working months begins. For example, if an individual who worked four months during the year is randomly assigned the number ten, the individual's empioyment status for October, November, December, and January is set to "working. The second random number determines the month in which a consecutive string of unemployed months begins. If the individual in our example was unemployed for five months, we would randomly draw a number between two and five. If the individual is randomly assigned the number four, the individual's employment status for April, May, June, July, and August is set to "unemployed." The individual's employment status for the remaining months of the year (February, March, and September) is set to "not in the labor force." Once the employment status for each month is assigned, earnings are distributed evenly over months designated as working months.

Annual unemployment compensation is allocated evenly over months in which the individual's employment status is "unemployed." If unemployment compensation is reported yet the individual worked more than 50 weeks in the year, the amount of unemployment compensation is allocated evenly over the entire year.

Prior to the March 1989 CPS, amounts received for unemployment compensation were lumped together with amounts received for veterans' benefits and workers' compensation, while receipt was identified separately. When amounts are lumped together, we allocate the lump-sum amount to component sources before we allocate annual benefits to months. If the receipt of benefits from all three sources was reported, we allocate 40 percent of the total to veterans' benefits, 21 percent to unemployment compensation, and the balance (39 percent) to workers' compensation. If the receipt of benefits from two of the three sources was reported, we allocate the total amount received as follows:

- Veterans' benefits (65 percent) and unemployment compensation (35 percent)

- Veterans' benefits (51 percent) and workers' compensation (49 percent)
- Unemployment compensation (36 percent) and workers' compensation (64percent)

These allocation percentages reflect relative differences in average amounts for persons in the March 1985 CPS receiving income from one of these sources.

The allocation across months of noncash transfers and other nonasset income, such as Social Security, pensions, workers' compensation, and veterans'henefits, depends on the individual's age and the type of income in question. (Workers' compensation and veterans' benefits are first separated from unemployment compensation if necessary.) For recipients age 60 and older, we allocate any reported amount of noncash transfers or other nonasset income evenly over the full year. For nonelderly recipient& we use a three-step allocation procedure. In the first step, we randomly determine the number of months in which the income source was received, based on probabilities developed by Doyle (1984) that vary by type of income In the second step, we randomly select a month and assume that the period of receipt began with that month In the third step, we allocate the amount received evenly over the assigned period of receipt. The second and third steps are used to allocate income from earnings, as noted before.

Cash welfare (AFDC, SSI, and GA) and asset income are allocated evenly over the full year. Siiulation of intrayear fluctuations is beyond the scope of this study.

At this stage, we add to the CPS extract file three new variables needed to simulate FSP eligibility. The food stamp unit size is the size of the Census household minus SSI recipients in SSI cashout States (California and Wisconsin) who received cash instead of food stamps. The gross monthly income of the food stamp unit is the sum of the monthly incomes of members of the unit. Asset balances are imputed by dividing the sum of annual income from interest-bearing accounts, rental property, and other assets by a rate of return of 6.5 percent (Thus, asset balances are just over 15 times asset income.)

STEP THREE: IMPUTING NET INCOME

Simulating food stamp program eligibility requires information on net income, gross income, and asset balances for each household Although gross income is available from CPS data and asset balances can be imputed from CPS data on asset income as described above, the CPS data contain no information on net income, which is gross income less allowable deductions. We impute net income using a regression model relating net income to each food stamp unit's earnings, unearned income, and geographic location. We estimate separate regression equations for each year using ordinary least squares (OLS) and data from a merged July/August Integrated Quality Control System (IQCS) file. Households residing in Puerto Rico, Guam, and the Virgin Islands are excluded from the IQCS file Earned income tax credit (EITC) inwme is excluded from household income.

Net income for each food stamp unit in the CPS with gross income greater than zero is imputed using the following equation:

NETINC = INTERCEPT + B1(TMEARN) + B2(TMEARN**2) +
B3(UNEARN) + B4(UNEARN**2) + B5(GRSFLG) +
B6(ALASKA) + B7(HAWAII) + B8(MIDWEST) +
B9(SOUTH) + B10(WEST) + ERR,

where INTERCEPT and B1-B10 are estimated regression coefficients and ERR is a normally distributed random variable with mean equal to 0 and, for 1989, standard deviation equal to 75.41451. The right-hand-side variables in the imputation equation are defined as follows:

- TMEARN-monthly household earnings
- TMEARN**2--monthly household earnings squared
- UNEARN-monthly household unearned income
- UNEARN**2--monthly household unearned income squared

- **GRSFLG--dummy** variable equal to one if household gross income is $100 or less
- **ALASKA--dummy** variable equal to one for households residing in Alaska
- HAWAII-dummy variable equal to one for households residing in Hawaii
- **MIDWEST--dummy** variable for **households residing** in Midwest region
- **SOUTH--dummy variable for** households **residing** in South region
- WEST-dummy variable for households residing in West region

Net income is imputed (and **FSP** eligibility status **is** simulated) for the month of August. Net income is constrained to be greater than or equal to zero and less than gross income minus the food **stamp standard** deduction. The Midwest region contains the East North Central and West North Central census divisions; the South region contains the West South Central, Fast South Central, and South Atlantic census divisions; and the West region contains the **Pacific** and Mountain census divisions. The States contained in each of these census **divisions** are listed in Table **V.1** in Chapter V.

STEP **FOUR:** SIMULATING **FSP** ELIGIBILITY STATUS

Unless exempt, households must pass a gross income test, a net income test, and an asset test to be eligible for the FSP. Households in which all members receive public assistance (AFDC, **SSI,** or **GA)** were exempt from all three tests in 1989 and **were** automatically eligible for the FSP. Households with elderly or disabled members were exempt from the gross income **test.** The gross income test for 1989 excluded from the **FSP** households with gross income greater than 130 percent of the Federal poverty guidelines. The net income test sets **a maximum** value for a food stamp unit's monthly net income based on the size of the unit and its state of residence (continental United States, Alaska, or Hawaii). To be eligiile for the FSP, a household with an elderly member could **not have owned assets valued at more than $3,000 in 1989. The asset limit was $2,000 for all other** households. For simulating FSP **eligibility** status, our **gross income test is** based on amounts **recorded** in the CPS data. Our asset and net income tests use imputed assets and imputed net income, each derived as described above.

Once the FSP eligibility status is determined for a household in the CPS, a new household level file is created by adding to the original household level input file several variables, including a variable indicating whether the household is eligible for the FSP. To obtain estimates of eligible persons from the household file, a person weight is calculated by multiplying the household weight from the CPS by the number of persons in the household. Summing these weights over all households in a State yields an estimate of the number of individuals eligible for the FSP.

APPENDIX B

SYMPTOMATIC INDICATORS FOR REGRESSION MODELS

The symptomatic indicators used in our regression models are listed in Table B.l with their definitions and sources. State totals for each indicator are based on administrative records and, thus, are not subject to sampling error. All sources are published annually; data used in this study pertain to 1986, 1987, and 1988.

AFDC, SSI, and INCOME-reported as counts-are converted into proportions or per capita figures by dividing by the resident population of each State as of July 1. State resident population totals are obtained from Census Bureau estimates (U.S. Bureau of the Census. "State Population and Household Estimates, With Age, Sex, and Components of Change: 1981-88." *Current Population* Reports, series P-25, no. 1044, August 1989, p. 13. Table 1, "Estimates of the Resident Population of States"). The Federal Bureau of Investigation used the same State population estimates to calculate State crime rates.

LOWBIRTH includes births of unreported weight in each State, which are allocated according to the reported ratio of low birthweight births to normal birthweight births in that State.

In each year, OILGAS equals one for Louisiana, Oklahoma, Texas, Wyoming, Colorado, New Mexico, and Alaska and zero for all other States.

TABLE B.l

SYMPTOMATIC INDICATORS

Symptomatic Indicator	Definition	Source
AFDC	The proportion of individuals in the State receiving Aid to Families with Dependent Children	U.S. Department of Health and Human Services, Social Security Administration. *Social Security Bulletin, Annual Statistical Supplement.* Washington, D.C.: U.S. Government Printing Office, 1988, 1989, 1990. Table 9.G2, 'Average monthly number of families and recipients of cash payments and total amount of payments, by State."
SSI	The proportion of individuals in the State receiving Supplemental Security Income	U.S. Department of Health and Human Services, Social Security Administration, Social *Security Bulletin, Annual Statistical Supplement.* Washington, D.C.: U.S. Government printing Office, 1987, 1988, 1989. Table 9.B1, "Number of persons receiving federally administered payments and total amount of payments, by reason for eligibility.
INCOME	State per capita total personal income (millions of dollars per person)	Regional Economic Measurement Division. State Personal Income, 1986-1988: Revised Estimates." *Survey of Current Business,* vol. 69, no. 8, August 1989, pp. 33-56; and "State Personal Income, 1987-1989: Revised Estimates." Survey *of Current Business,* vol. 70, no. 8, August 1990, pp 27-40. Table 1, "Total and Per Capita Personal Income by States and Regions."
CRIME	The State crime rate (number of violent and property crimes per 100,000 population)	U.S. Bureau of the Census. *Statistical Abstract of the United States.* Washington, D.C.: U.S. Government Printing Office, 1988, 1989, 1990. Table 279, "Crime Rates by State." Source: U.S. Federal Bureau of Investigation, *Crime in* the united states, annual.
LOWBIRTH	Low birthweight births (less than 2,500 grams) as a proportion of all live births in the State	U.S. National Center for Health Statistics, *Vi Statistics of the United States.* Washington, D.C: us. Government Printing Office, 1987, 1988, 1989. Table 22

TABLE B.l (continued)

Symptomatic Indicator	Definition	Source
OILGAS	**Dummy** variable equal to one if one percent or more of the State's total **personal income is** attributable to the oil and gas extraction industry	Regional Economic Measurement Division. "State Personal Income, **1986-1988:** Revised Estimates.' ***Survey of Current Business*, vol. 69, no. 8, August 1989,** pp. **33-56;** and **"State** Personal **Income, 1987-1989:** Revised **Estimates."** ***Survey*** of ***Current Business*,** vol. 70, no. 8, August 1990, **pp 27-40.** Table 3, "Personal Income by Major Sources."
UNEWENG	Dummy variable equal to one for the New England States	Maine, New Hampshire, Vermont, Massachusetts, and Rhode Island (the New England **Census** division minus Connecticut)

APPENDIX C

THE BEST REGRESSION MODELS

This appendix presents the regression models identified as the best models by our model fitting procedure. The **model** fitting procedure is descrii in Chapter IV. Symptomatic indicators are defined in Appendix B.

The best poverty rate regression model for **1986 is:**

POVRATE = 0.24 + 26 SSI – 0.0100 INCOME + 0.024 **OILGAS** – 0.041 UNEWENG

(R^2 = 0.85)

The best poverty rate regression model for 1987 is:

POVRATE = 0.20 + 3.2 SSI – **0.0077** INCOME + 0.025 **OILGAS** – 0.037 UNEWENG

(R^2 = 0.82)

The best poverty rate regression model for 1988 is:

POVRATE = 0.15 + 3.8 SSI – 0.0071 INCOME + 0.033 **OILGAS** – 04000046 **CRIME**

(R^2 = 0.85)

The best FSP eligibility rate regression model for 1986 is:

ELIGRATE = 0.25 + 3.7 SSI – 0.010 INCOME + 0.031 **OILGAS** – 0.046 UNEWENG

(R^2 = 0.84)

The best FSP eligibility **rate regression mode1 for 1987 is:**

ELIGRATE = 0.23 + 3.9 SSI – 0.0094 **INCOME** + 0.026 **OILGAS** – 0.042 **UNEWENG**

(R^2 = 0.83)

The best **FSP eligibility** rate **regression model** for 1988 **is:**

$$\textbf{ELIGRATE} = 0.18 + 4.5\ \text{SSI} - 0.0070\ \text{INCOME} + 0.046\ \textbf{OILGAS} - 0.022\ \text{UNEWENG}$$

$$(R^2 = 0.85)$$

In each of the six models, the t-statistics for **all** coefficients on symptomatic indicators are greater than 2.0.