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THE EFFECT OF CASELOAD CHARACTERISTICS AND SOCIOECONOMIC CONDITIONS ON FOOD STAMP PAYMENT ERROR RATES

FINAL REPORT

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EXECUTIVE SUMMARY

PURPOSE

The Food Security Act of 1985 (P.L. 99-198) required the Secretary of Agriculture to conduct a study of the Quality Control (QC) system currently in use for the Food Stamp Program. The law mandated that "the study shall examine how best to operate such system in order to obtain information that will allow the State agencies to...provide reasonable data on the basis of which Federal funding may be withheld from State agencies with excessive levels of erroneous payments." This paper provides information that can be used to evaluate the basis on which States are held accountable for unacceptable levels of overpayments.

Under the current QC system, States are liable for overpayments which exceed a legislatively established threshold (currently set at 5 percent of total benefits paid), and all States are held to the same standard of acceptable overpayment error. Because this practice of equal treatment does not take into account the fact that States face different situations that may make it more, or less, difficult to reduce overpayments, some State administrators have maintained that the system is basically unfair. QC error rates may reflect not only the administrative performance of an agency, but also the difficulty of the caseload served and the characteristics of the operating environment -- factors that, it could be argued, are beyond the control of State and local managers. If some factors can be identified that have a clear and measurable effect on the difficulty of preventing error, it might be appropriate to adjust error rates or, equivalently, error thresholds to account for the differences among States. Such adjustments would then, in theory, provide a better measure of relative State performance; it would acknowledge the good performance of those States that have lowered their error rates in spite of facing difficult conditions.

To date, however, there has been no clear empirical evidence on which to base such adjustments. Furthermore, the distinction between which factors are controllable and which are uncontrollable is not always clear. Managers facing large, dynamic caseloads, for example, are likely to adopt a different set of administrative practices than managers facing small, stable caseloads. While these managers cannot control the size or stability of the food stamp population, they can control their response. States have been given substantial flexibility to put procedures in place which minimize overpayments, with the Federal government paying half the cost of administering the program. If States face different situations, then they may implement administrative procedures that are best suited to the particular causes of errors which are most prevalent in their States.

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Our purpose in this study was not to resolve the philosophical debate but to explore the practical aspects of the desire to adjust error rates for external factors. The objective was twofold: to determine if there are external factors such as caseload characteristics and socioeconomic conditions which account for observed differences in State QC payment error rates; and, if such factors do account for these differences, to evaluate the feasibility of developing a procedure to adjust error rates to compensate for their effect.

METHODOLOGY

The data used to examine these issues combined information from the Fiscal Year 1984 Integrated Quality Control System (data on individual participants) with information from the 1980 Census of Population and Housing (data on the characteristics of the area in which the participants reside). Payment error rates were decomposed into five parts: the probability of an overpayment error occurring; the amount of an overpayment error should one occur; the probability of an ineligibility error occurring; the amount of an ineligibility error should one occur; and the size of the food stamp allotment. Statistical models were developed for each component to examine the relationship between each of the five outcome measures and caseload and socioeconomic characteristics. The separate results were then combined to derive an adjusted payment error rate for each State. The adjusted rates were then compared to the State reported error rates to determine whether the two estimates were significantly different. Finally, the sensitivity of the statistical procedures was examined by varying the specification of the different models (i.e., changing the variables that were included) and by replicating the analysis on data for Fiscal Year 1985 to assess the extent to which the results would be stable from year to year.

RESULTS

The analysis described in this paper yields the following findings:

- Some caseload and local area socioeconomic characteristics are statistically significant predictors of both the incidence and amount of overpayments and/or issuances to ineligible households. These include: household size, the presence and source of income and assets, the number of deductions, and the density of the population around the local office area in which a household resides. However, some important variables, particularly measures of caseload dynamics, could not be included in the analysis. In their absence, only part of the effect of caseload characteristics on payment error is captured by these models.

- Accounting for the effect of these factors produces adjusted error rates that are statistically different from State reported error rates; on an individual State basis, the adjustments are statistically significant for 30 percent of the States (i.e., 15 out of 50).

- The adjustment procedure produces relatively large adjustments to State reported payment error rates: the average error rate is about 8 percent, and the adjustments range from almost -3 percent to approximately +2.5 percent. Adjustments of this magnitude can have a substantial effect upon a State's liability for erroneous payments. Applying the law currently in effect, the liabilities for 22 States would not be affected by the adjustments; but liabilities would be reduced for 16 States and increased for 12. Any change in liabilities is substantial in dollar terms: under existing law the minimum change has to be 5 percent of the federal share of a State's administrative costs. Some of the changes would be quite large: for five States, the adjustment would add liabilities of 20-25 percent of their federal administrative costs; two would have reductions in liabilities of similar magnitude.

- The results reported here yield adjustments that are much different from those associated with two recently introduced legislative proposals (H.R. 1279 and H.R. 2621). Moreover, the correlation between the adjustments derived from the two legislative proposals is quite low as is the correlation between them and the adjustments calculated from our empirically-based adjustment procedure.

- Small changes in the analysis procedures can make important differences in the resulting adjustments for some States. The calculated adjustments to State payment error rates were based only on one of many statistical models developed from the same data during the course of this analysis. In a purely statistical sense, many of these other models performed equally well: the explanatory power was roughly the same, the correlation between the different adjustments was reasonably high, and the regression coefficients were significant. However, for a few States the adjustments

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produced by these alternatives were found to be sufficiently different to have an important effect on their liability for erroneous payments.

- The exclusion of an important variable from the models was found to produce adjustments that are substantially different for a large number of States. Because a class of potentially important factors--measures of caseload dynamics--could not be included in this analysis (due to data limitations), proceeding with the models presently available might entail compensating States on the basis of a seriously inaccurate picture of the caseload and socioeconomic characteristics that make controlling payment errors more, or less, difficult.

- To be acceptable, an adjustment procedure should also be relatively stable from one year to the next; wide swings in the size or direction of error-rate adjustments would probably raise serious questions about the fairness or usefulness of the entire adjustment process. Comparing adjustments computed for Fiscal Year 1984 and Fiscal Year 1985, we found ten States with large changes (i.e., more than one percentage point) in the adjustments from one year to the next. In seven of these ten States, the direction of the adjustment changed; it was positive in one year and negative in the other. Twenty other States experienced moderate changes (more than half but less than a full percentage point). And in another 20 States the difference between the 1984 and 1985 adjustments was less than half a percentage point. Although these changes are largely due to sampling variability that affects even current procedures for calculating State error rates, the complexity of the adjustment procedure may make these differences seem more arbitrary to State administrators. The effect of these changes is often large enough to make a substantial difference in a State's financial liability. For example, New York's error rate would have been adjusted upward by 0.8 percentage points in 1984 but by 2.3 points based on the 1985 sample. The difference in the adjustment would have meant a difference of about $12 million in financial liability.

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Considerable progress has been made in identifying factors that contribute to variations in error rates. Accounting for the effect of these factors yields adjusted error rates that are reliably different from the original State-reported error rates for 30 percent of the States. Moreover, the magnitude of these adjustments is large enough to have an important effect upon the fiscal liabilities of some States.

The statistical models on which the adjustments are based are sensitive to the exclusion of important measures of State caseload and socioeconomic characteristics. Because we know we have excluded a potentially important class of variables from this analysis (i.e., caseload dynamics), proceeding with our current models might result in inequities by compensating States on the basis of an incomplete picture of the underlying causes of payment errors. In light of this, we believe that the adjustments will not necessarily produce error rates that are more equitable. Rather than improving the current system, the adjustments could simply exacerbate the debate over the fairness of withholding funds from States with excessive levels of erroneous payments.

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I INTRODUCTION

The Food Security Act of 1985 (P.L. 99-198) requires the Secretary of Agriculture to conduct a study of the Quality Control (QC) system currently in use for the Food Stamp Program. The law prescribes two distinct objectives for this review, mandating that "the study shall examine how best to operate such system in order to obtain information that will allow the State agencies to improve the quality of administration and provide reasonable data on the basis of which Federal funding may be withheld from State agencies with excessive levels of erroneous payments."

This paper has been prepared to support the second of these objectives, to provide information that can be used to evaluate the basis on which States are held accountable for unacceptable levels of overpayments.1/ Under the current QC system, States are liable for overpayments which exceed a legislatively established threshold (now set at 5 percent of total benefits paid). For the most part, all States are held to the same standard of acceptable administrative error. This practice, however, does not take into account the possibility that States may face different situations that may make it more, or less, difficult to control overpayments. For example, some cases may be inherently more difficult to administer, thereby increasing the likelihood of error; States with a greater proportion of such cases may, as a result, find it harder to achieve a low error rate.

Some State administrators have maintained that the practice of equal treatment is basically unfair. QC error rates may reflect not only the administrative performance of an agency, but also the difficulty of the caseload served and the characteristics of the operating environment -- factors that, it could be argued, are beyond the control of State and local managers. If some factors can be identified that have a clear and measurable effect on the difficulty of preventing error, it might be appropriate to adjust error rates or, equivalently, error thresholds to account for the differences between States. Such adjustment would then, in theory, provide a

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1/Although the QC system is used to examine both underpayments and overpayments to beneficiaries, we have focused only on the latter type of errors. Because overpayment errors (including both excessive payments to eligible cases and payments to ineligible households) are used to assess State liabilities, they have been the central aspect of the debate over the fairness of the existing system.

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better measure of relative State performance; it would acknowledge the good performance of those States that have lowered their error rates in spite of facing different conditions.

To date, however, there has been no clear empirical evidence on which to base such adjustments. Furthermore, the distinction between which factors are administratively controllable and which are uncontrollable is not always clear. Managers facing large, dynamic caseloads, for example, are likely to adopt a different set of administrative practices than managers facing small, stable caseloads. While these managers cannot control the size or stability of the food stamp population, they can control their response. States have been given flexibility to put procedures in place which minimize overpayments, with the Federal government paying half the cost of administering the program. If States face different situations, then they should implement administrative procedures that are best suited to the particular causes of errors which are most prevalent in their States.

Our purpose, then, is twofold: to determine if there are external factors such as caseload characteristics and socioeconomic conditions which account for observed differences in State QC payment error rates; and, if such factors do account for these differences, to evaluate the feasibility of developing a procedure to adjust error rates to compensate for their effect.

The Quality Control System

The Food Stamp Program provides food assistance benefits to households that meet eligibility requirements based on income, household size and assets (e.g., bank accounts, vehicles, etc.). Benefits are issued in the form of coupons which eligible households can use to purchase food from approved retail stores.

The program is administered by the U.S. Department of Agriculture, Food and Nutrition Service (FNS), which provides 100 percent financing for the food stamp benefits ($10.8 billion in fiscal year 1985) and 50 percent financing for the States' administrative expenses (about $900 million in fiscal year 1985).

In order to ensure that food stamp benefits are provided to those households that are, in fact, eligible, Congress mandated the QC system as part of the Food Stamp Act of 1977 (a similar system had already been in use under regulations issued in

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1971). The QC system focuses on the accuracy of household eligibility and benefit determinations. It provides two general measures of certification accuracy for each State.2/ The first is based on an intensive review of a probability sample of Food Stamp Program participants. These reviews determine whether the participating household is eligible and receiving the correct food stamp benefit -- neither more nor less -- given its income, expenses, resources, and living arrangements. The second measure is based on a sample of households whose application for food stamps has been denied or whose benefits have been terminated. These reviews of "negative actions" determine whether the decision to deny or terminate was based on correct procedures.

The current QC process is conducted in two parts: the State review and the federal re-review. In the State review process, samples of food stamp households are selected, and State QC staff conduct intensive reviews of each case to determine if the eligibility and benefit decisions recorded in the case file were based on an accurate assessment of household circumstances and correct application of food stamp policy. The results of State reviews for each case are recorded on QC review schedules (see Appendix A) and transmitted to the Food and Nutrition Service (FNS) of the Department of Agriculture. Based on the State review results, a reported error rate is computed.

The federal re-review establishes an official error rate, which is the basis for assessing liabilities and offering incentives for State performance. Federal QC staff in each FNS Regional Office select a sub-sample of the cases reviewed by State QC staff, and conduct their own review to determine if household circumstances were correctly evaluated and eligibility policy correctly applied. The results of the federal re-review are recorded for each case in this subsample; these results may differ from the State review results for particular cases.

2/Includes the 50 States plus the District of Columbia, Guam and the U.S. Virgin Islands. Puerto Rico is not included because, in July 1982, its Food Stamp Program was replaced with an annual block grant.

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The official error rate, calculated on a federal fiscal year basis3/, is based on the results of both the federal and State reviews using a "regression estimator"4/. This estimate corresponds to the error rate that would result if the federal QC review, preceded by a State review, were applied to the entire caseload. The estimate is further refined to adjust for the percentage of cases in the original State sample for which reviews were not completed. This second adjustment is intended to maximize incentives for completion of reviews at the State level (Appendix B provides State-by-State regressed error rates for Fiscal Year 1984).

The Food Stamp Act Amendments of 1982 established a liability system based on the regressed payment error rate that is determined for each State. Under this system, the regressed error rate is compared to a Congressionally mandated target or threshold. States are financially liable for error rates that exceed the threshold, however, States with error rates below the threshold can receive incentives in the form of enhanced federal reimbursements under certain circumstances. The assessment of liabilities provides a mechanism by which both State and federal governments share in the cost of certification error. Because food stamp benefits are fully funded by federal tax dollars, the federal government would bear the full cost of all erroneous payments in the absence of quality control liabilities. Quality control liabilities limit federal fiscal participation in erroneous benefits, thereby redistributing some of the risk of erroneous certification decisions to State and local agencies. In 1985 alone, the cost of erroneous overpayments was nearly $900 million of which States were held accountable for less than 25 percent.

3/Prior to fiscal year 1983, States made reviews and compiled and reported results for 6-month periods beginning each October and April. Since then the official Food Stamp Program error rate has been reported on an annual basis.

4/See Hansen, Morris H. and Benjamin J. Tepping, "A Statistical Evaluation of Food Stamp Quality Control", Westat Inc. (forthcoming)

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For Fiscal Year 1984 (the year covered by the analyses reported in this paper), most States had a 7 percent error rate "threshold" and were generally liable for any overpayments that exceeded 7 percent of the total benefits they had issued during that year.5/ For Fiscal Year 1985 and each subsequent year, the error rate threshold was reduced to 5 percent (see Exhibit 1.1). A State's liability is equal to 5 percent of its federally reimbursed administrative costs for each of the first 3 percentage points (or fractions thereof) by which the State's overpayment error rate exceeds the threshold and 10 percent for each additional percentage point or fraction thereof. For example, Wisconsin, which had a 9.6 percent error rate in Fiscal Year 1984, was liable for an amount equal to 15 percent of its Fiscal Year 1984 federal reimbursement for administrative costs--5 percent for each of the 3 percentage points (or fractions thereof) by which it exceeded its 7 percent threshold. Alabama, whose error rate was 13.4 percent in Fiscal Year 1984, was liable for an amount equal to 55 percent of its Fiscal Year 1984 administrative reimbursement--15 percent for the first 3 percentage points in excess of the 7 percent threshold plus 40 percent for the additional 4 percentage points. In no circumstance, however, can the amount

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EXHIBIT 1.1

State Regressed Payment Error Rates, Thresholds, and Liabilities: Fiscal Years 1984 and 1985

State	Fiscal Year 1984 Error Rate (percent)	Fiscal Year 1984 Threshold (percent)	Fiscal Year 1984 Liability	Fiscal Year 1985 Error Rate (percent	Fiscal Year 1985 Threshold (percent	Fiscal Year 1985 Liability
Alabama	13.35	7.00	$9,221,622	13.50	5.00	$13,118,714
Alaska	9.29	10.45	none	13.53	5.00	2,096,078
Arizona	9.38	8.36	1,199,017	9.38	5.00	4,329,756
Arkansas	9.66	7.00	1,144,268	7.88	5.00	1,242,979
California	7.67	7.00	4,263,749	7.08	5.00	13,136,972
Colorado	10.66	7.25	1,381,910	8.48	5.00	1,354,275
Connecticut	7.11	8.04	none	7.04	5.00	1,025,885
Delaware	6.40	7.00	none	7.17	5.00	246,819
District of Columbia	8.80	7.93	235,823	9.81	5.00	1,561,937
Florida	8.95	7.48	2,116,453	6.71	5.00	2,432,062
Georgia	9.56	7.00	3,697,445	12.91	5.00	16,441,248
Guam	3.39	7.00	none	5.33	5.00	27,912
Hawaii	3.69	7.00	none	4.35	5.00	none
Idaho	6.88	7.00	none	5.16	5.00	57,098
Illinois	8.31	7.00	2,844,492	8.16	5.00	9,029,457
Indiana	8.64	7.00	1,361,069	10.90	5.00	5,659,493
Iowa	8.51	7.00	690,194	8.41	5.00	2,028,618
Kansas	7.35	7.20	101,150	8.16	5.00	1,078,122
Kentucky	8.98	7.00	1,395,355	6.00	5.00	776,939
Louisiana	10.16	7.00	5,283,439	9.76	5.00	7,719,113
Maine	6.74	7.00	none	7.91	5.00	598,696
Maryland	6.85	7.91	none	7.37	5.00	2,531,992
Massachusetts	9.86	7.45	2,321,093	9.71	5.00	5,860,198
Michigan	6.46	7.00	none	7.35	5.00	4,563,908
Minnesota	9.77	7.00	1,461,779	9.51	5.00	3,218,338
Mississippi	9.24	7.00	1,731,884	7.98	5.00	1,816,892
Missouri	5.83	7.00	none	5.23	5.00	487,902
Montana	8.77	8.46	90,933	7.44	5.00	385,539
Nebraska	8.40	7.00	301,193	9.04	5.00	1,152,601
Nevada	2.54	7.00	none	2.48	5.00	none
New Hampshire	8.18	7.76	73,631	4.42	5.00	none
New Jersey	7.47	7.00	1,008,471	8.50	5.00	5,829,207
New Mexico	11.83	7.60	2,197,196	8.83	5.00	1,620,452
New York	10.14	8.34	10,063,964	7.11	5.00	16,280,441
North Carolina	7.22	7.00	523,964	6.49	5.00	1,802,557
North Dakota	6.27	7.00	none	3.53	5.00	none
Ohio	6.65	7.00	none	7.43	5.00	3,690,595
Oklahoma	7.61	7.00	586,756	10.58	5.00	5,312,273
Oregon	9.18	7.00	1,340,292	9.41	5.00	3,800,149
Pennsylvania	10.41	7.00	7,819,005	9.36	5.00	11,709,304
Rhode Island	7.08	7.25	none	8.00	5.00	391,265
South Carolina	10.80	7.00	3,159,387	12.10	5.00	8,319,451
South Dakota	3.59	7.00	none	3.15	5.00	none
Tennessee	6.09	7.27	none	6.39	5.00	2,058,553
Texas	9.97	7.00	8,212,334	10.38	5.00	28,120,597
Utah	11.37	7.00	1,334,155	7.26	5.00	583,204
Vermont	9.71	7.00	200,169	8.06	5.00	410,263
Virginia	7.63	7.00	652,347	6.67	5.00	1,415,766
Virgin Islands	12.13	8.32	259,762	9.73	5.00	299,390
Washington	9.23	7.00	1,509,980	9.50	5.00	4,048,211
West Virginia	6.95	7.00	none	5.07	5.00	111,525
Wisconsin	9.60	7.04	1,391,622	8.00	5.00	1,267,661
Wyoming	9.08	7.17	94,377	6.78	5.00	138,332
Total			$81,350,279			$201,189,415

Both official error rates and error rate thresholds have declined since the first liabilities were assessed in 1981. However, because error rates have not decreased as much as the thresholds, fiscal liabilities have been increasing. From Fiscal Years 1981-1985, the Food and Nutrition Service has made a total of 144 assessments on 50 States for about $339 million but only 4 of the 144 liabilities have been paid - 3 by Connecticut and 1 by Wyoming. Thirty-four assessments involving 20 States have been waived in full by FNS, 5 assessments were overturned by the Administrative Review Board, and 101 assessments involving 49 States are still pending. Of the 101 assessments that are pending, 84 have either just been announced (Fiscal Year 1985) or are under good cause review within FNS (Fiscal Year 1984); 11 are being appealed to the Administrative Review Board (Fiscal Year 1983); and 6 are in the courts (from Fiscal Years 1981 and 1982).

The Debate Over Adjusting State Error Rates

As discussed above, State error rates vary widely (e.g., in Fiscal Year 1984 Nevada had a payment error rate of 2.54 percent, whereas Alabama's rate was 13.35 percent). Some States have stated, however, that this variation is not completely attributable to differences in how well States administer the Food Stamp Program. Rather, they argue that their unique socioeconomic conditions and caseload composition result in a greater level of difficulty than is found in other States. Moreover, States have continually expressed concern that the existing QC system does not take such differences into account when determining State liabilities for overpayment errors. As noted by the American Public Welfare Association, "The legitimacy of sanctions depends on their being reasonably related to an accurate determination of payment error over which States have control."6/

In consideration of these concerns, two legislative proposals were recently introduced that would explicitly recognize that certain external factors influence error rates. The first, proposed by Congressman Robert Matsui (D-CA) in 1985 (H.R. 1279--The AFDC Error Reduction and Quality Control Improvement Act), focused on the AFDC program. The Matsui legislation put

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6/American Public Welfare Association, Briefing Book on Quality Control and Fiscal Sanctions in the AFDC, Medicaid and Food Stamp Programs, August 1985, p. 1.

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forth a plan to adjust each State's error rate threshold annually (from a base of 5 percent) for the effect of three such factors: an increase of 0.5 percent if the State extends AFDC benefits to children in families where both parents are unemployed (i.e., AFDC-U); an increase of 0.1 percent for each 20 percent increment that the proportion of the State's caseload with earned income exceeds the national average; and an increase of 0.1 percent for each 20 percent increment that the State's population density exceeds the national average. The second proposal, The Food Stamp Quality Control Bill of 1985, (H.R. 2621) was introduced in May, 1985 by Congressman James Jeffords (R-VT). The Jeffords proposal would also set the threshold at 5 percent but would adjust annually for four factors: the proportion of a State's caseload with earned income, the proportion with five or more persons in the household, the population density and the rate of caseload increase. For each 20 percent increment by which a State exceeds the national average (or in the case of population density, is also below the average), its threshold would be increased by 0.1 percent (not to exceed 0.5 for any one factor).

The effect these two proposals would have had on Fiscal Year 1984 State error thresholds for the Food Stamp Program is shown in Exhibit 1.2. Adjustments under H.R. 1279 range from a low of zero for Maine, Nevada, and New Hampshire to a high of one percent for Maryland, Missouri, New Jersey, and Pennsylvania. Adjustments under H.R. 2621 tend to be larger, ranging from a low of two-tenths of one percent for California and Colorado to a high of 1.1 percent for Oregon, South Dakota and Wyoming. The adjustments are, by design, all in one direction, i.e., error thresholds are all increased. More importantly, the two proposals tend to "reward" different States--the simple correlation between the two adjustments is only 0.32. For the most part, the largest contribution to the overall adjustment under H.R. 1279 is the presence of an AFDC-U program; the largest contribution under H.R. 2621 is the population density factor, which compensates both densely populated and sparsely populated States.7/

Given that two reasonable proposals for incorporating caseload and socioeconomic factors into the QC system produce such

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7/In Chapter 5, we will examine the effect of using these variables to develop statistical adjustment models.

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EXHIBIT 1.2: Comparison of FY84 State Food Stamp Payment Error Rate Thresholds to Adjusted Thresholds under two Legislative Proposals

			H.R. 1279[a]					H.R. 2621[b]				
			Adjustment Due to....					Adjustment Due to				
State	Required Threshold ($)	Official Error Rate	AFDC-U	Earnings	Population Density	Adjusted Threshold	Difference	Earnings	Population Density	Household Size	Adjusted Threshold	Difference
Alabama	7.00	13.35	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
Alaska	10.45	9.29	0.0	0.1	0.0	10.55	0.1	0.1	0.5	0.1	11.15	0.7
Arizona	8.36	9.38	0.0	0.2	0.0	8.56	0.2	0.2	0.5	0.2	9.26	0.9
Arkansas	7.00	9.66	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
California	7.00	7.67	0.5	0.0	0.1	7.60	0.6	0.0	0.1	0.1	7.20	0.2
Colorado	7.25	10.66	0.5	0.0	0.1	7.85	0.6	0.0	0.1	0.1	7.45	0.2
Connecticut	8.04	7.11	0.5	0.0	0.0	8.54	0.5	0.0	0.1	0.2	8.34	0.3
Delaware	7.00	6.40	0.5	0.1	0.0	7.60	0.6	0.1	0.3	0.1	7.50	0.5
District of Columbia	7.93	8.80	0.0	0.0	0.5	8.43	0.5	0.0	0.5	0.2	8.63	0.7
Florida	7.48	8.95	0.0	0.1	0.0	7.58	0.1	0.1	0.3	0.1	7.98	0.5
Georgia	7.00	9.56	0.0	0.2	0.0	7.20	0.2	0.2	0.4	0.2	7.80	0.8
Guam	7.00	3.39	0.5	0.5	NA	--	--	0.5	NA	0.5	--	--
Hawaii	7.00	3.69	0.5	0.1	0.0	7.60	0.6	0.1	0.2	0.1	7.40	0.4
Idaho	7.00	6.88	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
Illinois[c]	7.00	8.31	--	--	--	--	--	--	--	--	--	--
Indiana	7.00	8.64	0.0	0.2	0.0	7.20	0.2	0.2	0.3	0.2	7.70	0.7
Iowa	7.00	8.51	0.5	0.2	0.0	7.70	0.7	0.2	0.5	0.2	7.90	0.9
Kansas	7.20	7.35	0.5	0.1	0.0	7.80	0.6	0.1	0.4	0.1	7.80	0.6
Kentucky	7.00	8.98	0.0	0.2	0.0	7.20	0.2	0.2	0.4	0.2	7.80	0.8
Louisiana	7.00	10.16	0.0	0.1	0.0	7.10	0.1	0.1	0.5	0.1	7.70	0.7

EXHIBIT 1.2: Comparison of FY84 State Food Stamp Payment Error Rate Thresholds to Adjusted Thresholds under two Legislative Proposals (continued)

			H.R. 1279[a]					H.R. 2621[b]				
			Adjustment Due to.....					Adjustment Due to				
State	Required Threshold ($)	Official Error Rate	AFDC-U	Earnings	Population Density	Adjusted Threshold	Difference	Earnings	Population Density	Household Size	Adjusted Threshold	Difference
Maine	7.00	6.7	0.0	0.0	0.0	7.00	0.0	0.0	0.5	0.1	7.60	0.6
Maryland	7.91	6.85	0.5	0.0	0.5	8.91	1.0	0.0	0.5	0.2	8.61	0.7
Massachusetts	7.45	9.86	0.5	0.0	0.0	7.95	0.5	0.0	0.1	0.2	7.75	0.3
Michigan	7.00	6.46	0.5	0.0	0.3	7.80	0.8	0.0	0.3	0.3	7.60	0.6
Minnesota	7.00	9.77	0.5	0.1	0.0	7.60	0.6	0.1	0.2	0.1	7.40	0.4
Mississippi	7.00	9.24	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
Missouri	7.00	5.83	0.5	0.1	0.4	8.00	1.0	0.1	0.4	0.1	7.60	0.6
Montana	8.46	8.77	0.0	0.2	0.0	8.66	0.2	0.2	0.5	0.2	9.36	0.9
Nebraska	7.00	8.40	0.5	0.2	0.0	7.70	0.7	0.2	0.4	0.2	7.80	0.8
Nevada	7.00	2.54	0.0	0.0	0.0	7.00	0.0	0.0	0.5	0.1	7.60	0.6
New Hampshire	7.76	8.18	0.0	0.0	0.0	7.76	0.0	0.0	0.5	0.1	8.36	0.6
New Jersey	7.00	7.47	0.5	0.0	0.5	8.00	1.0	0.0	0.5	0.2	7.70	0.7
New Mexico	7.60	11.83	0.0	0.2	0.0	7.80	0.2	0.2	0.5	0.2	8.50	0.9
New York	8.34	10.14	0.5	0.0	0.0	8.85	0.5	0.0	0.2	0.3	8.84	0.5
North Carolina	7.00	7.22	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
North Dakota	7.00	6.27	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
Ohio	7.00	6.65	0.5	0.1	0.1	7.70	0.7	0.1	0.1	0.1	7.30	0.3
Oklahoma	7.00	7.61	0.0	0.1	0.0	7.10	0.1	0.1	0.5	0.1	7.70	0.7
Oregon	7.00	9.18	0.0	0.3	0.0	7.30	0.3	0.3	0.5	0.3	8.10	1.1
Pennsylvania	7.00	10.41	0.5	0.0	0.5	8.00	1.0	0.0	0.5	0.1	7.60	0.6

EXHIBIT 1.2: Comparison of FY84 State Food Stamp Payment Error Rate Thresholds to Adjusted Thresholds under two Legislative Proposals (continued)

			H.R. 1279[a]					H.R. 2621[b]				
			Adjustment Due to.....					Adjustment Due to				
State	Required Threshold (%)	Official Error Rate	AFDC-U	Earnings	Population Density	Adjusted Threshold	Difference	Earnings	Population Density	Household Size	Adjusted Threshold	Difference
Rhode Island	7.25	7.08	0.5	0.0	0.1	7.85	0.6	0.0	0.1	0.2	7.55	0.3
South Carolina	7.00	10.80	0.0	0.2	0.0	7.20	0.2	0.2	0.5	0.2	7.90	0.9
South Dakota	7.00	3.59	0.0	0.3	0.0	7.30	0.3	0.3	0.5	0.3	8.10	1.1
Tennessee	7.27	6.09	0.0	0.2	0.0	7.47	0.2	0.2	0.4	0.2	8.07	0.8
Texas	7.00	9.97	0.0	0.2	0.0	7.20	0.2	0.2	0.3	0.2	7.70	0.7
Utah	7.00	11.37	0.0	0.2	0.0	7.20	0.2	0.2	0.4	0.2	7.80	0.8
Vermont	7.00	9.71	0.5	0.1	0.0	7.60	0.6	0.1	0.5	0.1	7.70	0.7
Virgin Islands	8.32	7.63	0.0	0.7	NA	--	--	0.5	NA	0.5	--	--
Virginia	7.00	12.13	0.0	0.1	0.0	7.10	0.1	0.1	0.4	0.1	7.60	0.6
Washington	7.00	9.23	0.5	0.0	0.0	7.50	0.5	0.0	0.4	0.1	7.50	0.5
West Virginia	7.00	6.95	0.5	0.0	0.0	7.50	0.5	0.0	0.5	0.1	7.60	0.6
Wisconsin	7.04	9.60	0.5	0.1	0.2	7.84	0.8	0.1	0.2	0.1	7.44	0.4
Wyoming	7.17	9.08	0.0	0.3	0.0	7.47	0.3	0.3	0.5	0.3	8.27	1.1

a. Adjustments are as follows: presence of AFDC-U add 0.5 percent; for each 20% increment above national average of proportion of caseload with earnings add 0.1 percent; and, for each 20% increment above national average on population density add 0.1 percent.

b. Adjustments are as follows: for each 20% increment above the national average of proportion of caseload with earnings and proportion of caseload with 5 or more members add 0.1 percent; and, for each 20% increment above or below national average on population density add 0.1 percent. A final variable, rate of caseload increase, is not included because the national caseload was falling over this period and could not be defined.

c. Illinois was involved in a demonstration during FY84, hence, error rates are not comparable to other States. Because Illinois has been dropped from the analyses which follows, it has also been deleted from this table for consistency.

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disparate results, it would appear that such adjustments can be quite sensitive to the choice of measures used. But what criteria would a useful adjustment procedure have to meet to be acceptable?

The criteria flow largely from the use of the liability system as an incentive to program managers. The principal argument for adjusting State error rates is "fairness" -- that is, if two managers work equally effectively at controlling errors, and their results differ only because one manager faces a more difficult environment, they should be treated the same. From this it follows that,

- States with comparable circumstances should have roughly the same adjustment.

If the QC liability system is to provide incentives to managers to meet particular goals, they must know and understand the goals. The adjustment procedure should not obfuscate the goals, and hence,

- The basis for the adjustments should be understandable to program managers. They should know how characteristics of their operating environment affect their liability for overpayments. Ideally, the adjustment procedure would be "transparent" to a manager.

- The adjustment should not fluctuate dramatically from year to year (unless the operating environment fluctuates dramatically), because that would reduce managers' ability to know what goals they are trying to attain.

An adjustment procedure will inevitably reward some States and penalize (or fail to reward) others. For the procedure to be perceived as fair, particularly by those States that realize an increased liability for payment errors, the adjustments should result from a credible and reliable process. Therefore,

- The adjustment procedure should be technically sound and defensible, conforming to generally accepted statistical standards.

- The adjustment procedure must be reasonably robust. Small, equally defensible variations of the procedure -- for example, minor variations in the choice of factors used in the adjustment procedure -- should not produce substantially different adjustments.

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Any adjustment procedure will require considerable effort to implement each year, and even a procedure meeting the above criteria will probably be subject to some criticism. Hence, the final criterion is that,

- The procedure should produce adjusted error rates that are meaningfully different from those calculated in the current system. If the adjustments are trivial, they will not justify changing the system.

Organization Of This Report

The remainder of this report consists of four chapters. Chapter II reviews existing literature on the determinants of Food Stamp Program error rates. Chapter III presents the methodology used for the analysis discussed in this report, and Chapter IV describes the results. Chapter V examines the sensitivity of the models to changes in specification and the stability of the results from year to year.

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II. REVIEW OF THE LITERATURE ON DETERMINANTS OF FOOD STAMP ERROR RATES

The literature on the causes of error in the Food Stamp Program is relatively sparse. Somewhat more work has been done in analyzing AFDC errors, and many of the methods and findings of this literature can be used to think about the corresponding problem for food stamps.

This chapter reviews the relevant literature. Three sections are included: analyses of Food Stamp Program errors, analyses of AFDC errors, and implications for our current research.

Analyses Of Food Stamp Program Errors

With regard to the Food Stamp Program, three studies have examined the determinants of payment errors. Each is described below.

Budding (1983). In a report for the Food and Nutrition Service, David Budding8/ examined the likely effectiveness of different types of administrative actions to reduce payment errors. Using data from Massachusetts, Budding simulated the probability of errors occurring under four different types of administrative procedures: (1) methods designed to increase the effectiveness of the Food Stamp certification process, (2) methods designed to increase the probability that correct adjustments to benefits will be made when client circumstances change during the interim period between certifications, (3) methods which alter procedures for determining the length of the certification period and, therefore, alter the relative importance of certification and interim processes in the incidence of payment error, and (4) methods such as earnings cross-matches, designed to correct error outside the context of specific administrative actions.

Although the paper provides a number of important insights regarding the types of administrative procedures which are most likely to control error in the Food Stamp Program, one area in particular is especially relevant to our current efforts -- the dynamics of client characteristics.

As Budding points out, error is related not only to the characteristics of the households that comprise a State's

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8/Budding, David, Food Stamp Administrative Procedures and Issuance Error: A Theoretical Guide for Corrective Action, Abt Associates Inc., Cambridge, MA, March 1983.

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caseload, but also to the extent to which such characteristics change over time. This dynamic nature of the caseload is also an "uncontrollable" factor which can have a direct impact on the probability of a payment error, particularly after initial certification. A case which was correct at the time of initial certification may, as a result of changes in circumstances, later be found to be receiving erroneous benefits.

Explaining the interaction between the rate of change in client characteristics and the effectiveness of procedures designed to detect "interim" changes in circumstances, Budding reported that "If a local agency had an interim process which was capable on average of capturing two-thirds of all changes in client circumstances, that agency could have an interim error rate from 4 percent to 15 percent depending on the rate of change for clients. Conversely, to limit interim error to 5 percent, an administrator in a local office with infrequent changers would have to design an administrative process capable of capturing about 60 percent of all changes, while the administrator in an office with frequent changers would have to capture approximately 90 percent of all changes to limit interim error to the same level".9/ His admonition to program managers is that more frequent certifications or shorter certification periods for cases more likely to experience changes in circumstances may well produce a more immediate impact on error rates than more elaborate efforts to capture changes as they occur (such as monthly reporting).

Wood (1985). As part of the Illinois Monthly Reporting Demonstration project, an analysis10/ examined the effect of monthly reporting on four aspects of the Food Stamp Program: (1) changes in total caseload and benefit outlays, (2) payment accuracy, (3) administrative costs, and (4) recipient participation costs. Again, for our purposes, the analysis of payment accuracy is most relevant.

Using data from Illinois' QC reviews for the period October 1981 to September 1982, Wood estimated logit models to examine case error rates and regression models to explain error

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9/Ibid, p. 48.

10/Wood, Jean, Payment Accuracy and Error Rate Effects of Monthly Reporting in the Food Stamp Program, Abt Associates Inc., Cambridge, MA, June 1985.

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amounts. Covariates included in the models were an indicator for whether or not the case was subject to monthly reporting and various household characteristics. Monthly reporting did not appear to significantly affect error rates in any major way. The overall frequency of error and average error amount were not statistically distinguishable across treatment groups; there was no statistically significant effect on the probability of an overissuance, underissuance, or issuance to an ineligible case.

As in the AFDC monthly reporting experiments to be discussed later, a number of caseload characteristics were consistently related to higher rates of error: presence of two or more adults, presence of earned income, household size greater than or equal to five. In some instances, the presence of Supplemental Security Income (SSI), Retirement Survivor's and Disability Insurance (RSDI), pensions or other income was also found to significantly increase payment errors.

SRI International (1984). Probably the most relevant study conducted thus far is the analysis of the kinds, sources, and causes of error in the Food Stamp Program conducted by SRI International.11/ Using QC system data for 40 States for the period April 1981 through March 1982, the SRI report provides an excellent profile of payment errors:

- Among cases with errors, the average overpayment was about $53, consisting of payments to ineligibles (averaging about $93) and overissuances to eligibles (about $38).

- Errors related to the amount of the household's earned income were the largest source of errors (about one-third of the cases), followed by errors related to unearned income (about 24 percent) and deductions (about 20 percent). The majority of errors (about 58 percent of the cases) were client-caused, attributable largely to failure to report information. About 42 percent were agency-caused, attributable largely to failure to take action on reported information.

11/SRI International, Analysis of Case-Level Food Stamp Program Quality Control Data: A Special Topic Report of the Food Stamp Error Prevention Study, May 8, 1984.

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- Public Assistance (PA) and Non-public Assistance (NPA) cases had different error patterns. Compared to NPA cases, PA cases:

  -- contained slightly fewer overpayment errors (16.0 percent vs. 18.5 percent);

  -- involved somewhat larger average overpayment amounts ($57.31 vs. $50.58);

  -- were less likely to contain errors related to income or resources (56 percent vs. 71 percent), but more likely to contain errors related to deductions and household size (40 percent vs. 26 percent); and

  -- were more likely to involve agency-caused errors (48 percent vs. 38 percent).

In addition to describing the nature of overpayment errors, the authors also estimated multiple regression models to examine how household characteristics affect the likelihood and amount of error for five types of errors:

- overpayments, which were subdivided into:

  -- overissuances to eligibles, and
  -- payments to ineligibles;

- underpayments; and

- total error (the combination of overpayments and underpayments).

The case characteristics used in the analysis were drawn from the QC data and included: demographic characteristics; the presence of various types of income; deductions and resources; the food stamp allotment; and some measures of the frequency and recency of certification and recertification. Separate models were estimated for incidence and amount of error.

In general, household and case characteristics explained a relatively small portion of the variation in program errors--never more than 9 percent of the variation in errors among individuals and usually only about 3 percent of the variation. Although the combined explanatory power of household and case characteristics was small, some

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characteristics, nonetheless, had a statistically significant relationship to error:12/

- Households with more members had more overpayments and underpayments than households with fewer members.

- Households with a nonwhite head had more underpayments and more overissuances to eligibles than households with a white head (but whites and nonwhites differed little in payments to ineligibles).

- For all types of income except Supplemental Security Income, households with income had more overpayments and underpayments than did households without income.

- Characteristics that were related to the amount of overpayments were often related to the amount of underpayments. Thus, these characteristics appear to be indicators of a general tendency toward error, and overpayments to a group of people are partially offset by underpayments to people in the same group.

- Most characteristics were related to the amount of error and the incidence of error in a similar manner. Likewise, characteristics associated with overissuances to eligibles were usually associated with payments to ineligibles in the same direction. The only meaningful exception was household size: households with more members had higher payments to ineligibles but smaller overissuances to eligibles than did households with fewer members.

- The average amount of error was substantially higher several months after certification or recertification than at the time of, or in the first month after, recertification. The average error amount was higher when the most recent action was initial certification rather than recertification.

- These characteristics usually had a similar relationship to errors for both PA and NPA cases. The magnitude of the impact on errors of having earnings was substantially greater for PA cases than for NPA cases.

12/Ibid pp. 3-4.

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The authors, as indicated, generally discount their findings regarding the determinants of error on the basis of the low explanatory power of their models. The more meaningful criterion, however, would have been the reliability of the individual coefficients which, for the factors discussed above, were all highly statistically significant. Even though the overall explanatory power of the models may be low, the fact that individual caseload characteristics are reliable predictors of payment errors is an important finding.

Analyses Of AFDC Errors

In the AFDC Program, four main studies have, in recent years, examined the effect of various client and/or agency characteristics on error rates. Each is described below.

Bendick, Lavine, and Campbell (1978). Under a grant from the Social and Rehabilitation Service of the U.S. Department of Health, Education, and Welfare, the Urban Institute13/ examined the nature and extent of special problems associated with AFDC errors in urban areas. The goal of the study was to recommend roles for the federal government that would foster cost-

Two research approaches were used in the study. The primary approach examined Quality Control data from the fifty States and the District of Columbia for the period from 1974 to 1976 (five 6 month review periods). Ordinary least squares (OLS) regression was used to analyze variation in States' error rates, administrative costs and client accessibility. Site visits and discussions with State and local administrators were also used to provide insight into the difficulties of implementing corrective actions to reduce erroneous payments. The analysis that examined the factors affecting error rates is most relevant to this study.

In comparing the pattern exhibited by reported error rates between January - April 1974 and January - June 1976, the authors noted the wide variation that existed among the States

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- Administrative Practices. Agency policies on staffing (worker characteristics, workload, staff training and supervision), the amont and methods of verification of information, the frequency of eligibility redeterminations, etc.

- Benefit Policies. Complexity of rules used to calculate benefits, choice of what categories of persons are eligible for benefits (e.g., AFDC-U), the generosity of benefits, the leniency of eligibility criteria, etc.

- Environmental Cirumstance. Setting in which the agency operates ethnic and demographic characteristics of the client, physical and social setting, etc.

- Managerial Competence. Competence of individuals and organizations operating in a State.14/

The statistical analysis of error rates (both case and payment error) provided quantitative estimates of the impact of each of these sets of factors on error rates. The largest influential factor was found to be the administrative practices adopted by State agencies; accounting for 37 percent of all variation. Thirty-five percent of all variation was found to be due to environmental circumstances. Benefit policies accounted for an additional 8 percent. The remaining 20 percent was attributed to omitted factors (excluding administrative, benefit and environmental factors) that the authors were unable to represent in the statistical analysis, and "managerial competence which was measured as a residual factor--the remaining variation after differences in outcomes were attributed to the measurable factors. These findings led to the following conclusions:15/

> ...through control of administrative practices and benefit policies, states have considerable control over their error rates...it is also clear that different states, facing different environments, will experience different degrees of difficulty in meeting any nationwide uniform error rate standard or "tolerance level"...even if all states were to adopt the most efficient managerial practices, the most

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14/Ibid, p. 23.

15/Ibid, p. 25.

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error efficient managerial practices, and to recruit the most competent possible staff, circumstances somewhat beyond agencies' control (environmental factors) would still generate error, and differences in circumstances between states would still generate differences in error rates.

HEW's concern to identify special problems of urban areas led to specific analyses that were conducted to assess whether the circumstance of being urban vs. nonurban affected the difference in States' error rates. Comparing error rates among local areas within 8 States, the authors were unable to find a different error situation in large urban areas. While urban error rates were found to be, on average, slightly higher than nonurban rates, the differential was small and not consistant across States. The type of errors being made in urban areas were found to be substantially the same as those being made in nonurban areas. Moreover, variation among urban areas was found to be at least as substantial as that between all urban areas and all nonurban ones.

Mills (1982). Mills16/, using pooled data from the 1975-77 QC reviews, estimated an econometric model of AFDC under- and overpayment errors. The hypothesis was that observed interstate variation in AFDC error rates was a result of differences in the "production possibilities" of State welfare agencies (i.e., administrative actions to reduce errors) and their "administrative preferences" regarding the two types of error. According to Mills, States can take actions to control errors, but they cannot simultaneously reduce both types of error. "Any change....will cause a reduction in one type of error only at the expense of the other....if the agency seeks to reduce erroneous approvals simply by requiring a greater certainty of applicant eligibility, it must tolerate a higher incidence of erroneous denials."17/

Under this scenario, Mills sees the welfare agency's problem to be one of minimizing a "loss function" that reflects an

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16/Mills, Gregory, "Quality Control in AFDC: Explaining Interstate Variation in Payment Error Rates", The Urban Institute, Washington, D.C., Draft Working Paper, September 29, 1982.

17/bid, p. 4.

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increasing marginal rate of substitution between overpayments and underpayments, subject to the constraint of available administrative "inputs" affecting payment accuracy. That is, if a caseworker is shifted from error reviews to application processing, the overpayment error rate would drop but the underpayment error rate would increase. In this formulation, the optimum point for a particular agency is where the marginal rate of substitution between overpayments and underpayments (i.e., the tradeoff between the two types of error) equals the marginal rate of transformation between them (i.e., the change in inputs required to effect a unit change from one to the other).

Mills estimated his model on a pooled cross-sectional sample of 255 observations--one for each of fifty States and the District of Columbia for five consecutive semiannual periods covering July 1975 through December 1977. The outcome measure for each State was its federally-adjusted payment error rate (incorporating the Federal re-review findings). Two models were estimated, one dealing with administrative actions to reduce errors and one dealing with administrative preferences. Explanatory variables included in the first model pertained to <u>program policy characteristics</u> (e.g., federal matching rate for benefit payments, the use of a "consolidated grant" system, and the use of a "constrained benefit schedule"), <u>administrative characteristics</u> (e.g., ratio of staff to clients, frequency of client contact), <u>client characteristics</u> (e.g., urbanicity, educational level, presence of earned income), and the <u>intensity of quality control review</u> (e.g., number of reviews per reviewer, the time spent per review, the proportion of cases subject to Federal re-review). The explanatory variables included in the second model were associated with the extent to which the State was considered "pro- or anti-client." These factors included <u>financial characteristics</u> (e.g., State share of benefit payments, size of average grant), <u>staff and client characteristics</u> (degree of unionization of caseworkers, urbanicity, proportion of public assistance cases), and <u>regional location</u>.

The results of this analysis indicated a fairly severe tradeoff between the two types of error: a 1.0 percent <u>decrease</u> in the overpayment error rate is associated with a 2.3 percent <u>increase</u> in the rate of underpayments. This result, however, has not been supported by recent evidence on State error rates -- overpayment errors have dropped substantially with little

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corresponding change in underpayment errors. Because of program changes which have occurred since Mills' analysis it is unclear whether this lack of confirmation is due either to an inadequate theory or administrative actions which have altered the marginal rate of transformation found in the late 1970's. In Mills' analysis, four factors were systematically related to variations in State error rates over and above the effect of the administrative factors included in the models:

- States with a higher proportion of cases with earnings had higher error rates;
- States with clients having less schooling had higher error rates;
- States where the low-income population was more urban had higher error rates; and
- States with more public assistance cases had higher error rates.

Overall, the model explained 42.0 percent of the variation in the overpayment error rate and 28.5 percent of the variation in underpayments.

Hoaglin and Goodson (1984). In 1981, the Department of Health and Human Services (HHS) funded a series of projects designed to test the impact of monthly reporting in the Aid to Families with Dependent Children program (AFDC). In these projects, AFDC recipients were required to file monthly statements of their income and household circumstances, and the amount of their grant was based on a retrospective accounting principle (a previous month's income determines this month's grant). Abt Associates Inc., under contract to HHS, studied the effects of monthly reporting projects in Illinois, Massachusetts, and Michigan, comparing the monthly reporting system to the existing systems in those states.18/ The research focused on four issues: (1) the effect on total AFDC caseloads and payments, (2) the effect on administrative costs and structures, (3) the effect on recipients, and (4) the effect on

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18/Hoaglin, David and Barbara Goodson, Payment Accuracy and Error Rate Effects of Monthly Reporting for AFDC in Illinois, Abt Associates Inc., Cambridge, Massachusetts, April 1984.

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payment accuracy and error rates.19/ It is the last area that is relevant to this study.

The Illinois monthly reporting experiment randomly assigned AFDC cases in the Southeast District Office (in Cook County) among three groups. Cases in the monthly reporting group had to submit a completed Monthly Status Report (MSR) in order to continue receiving benefits, but they had no requirement for face-to-face redetermination. Cases in the variant group had the same monthly reporting requirement and were also expected to have an annual face-to-face interview. In the control group, only cases with some form of earned income had to make a monthly report, but all cases had a face-to-face redetermination at six-month intervals.

The overall findings of the experiment did not indicate any effect of monthly reporting on error rates; this result was consistent for both case and payment error rates and when error rates were decomposed into overpayments, underpayments and payments to ineligibles. The analysis, however, did examine the effect of particular caseload characteristics on error, and the results can inform our current modeling efforts.

Using a logit model to examine case error rates and a regression model to examine error amounts, this study examined the effect of monthly reporting on error rates, adjusting for the effect of various covariates. For the most part, these factors were "uncontrollable" in that they were related to characteristics of the caseload over which the Agency had no control. The results of the analysis indicated that five variables were significantly related to higher AFDC error rates: the presence of earned income, the presence of unearned income, household size, the education level of the primary caretaker, and having an unemployed father as the deprivation factor. The first two were found to be the most consistent and powerful predictors of both the incidence and amount of payment errors.

19/Abt Associates Inc. also studied the effect of monthly reporting on the Food Stamp Program in Illinois. These results were discussed earlier in this chapter.

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Ault et al.(1986). The Office of Income Assistance Policy, Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services recently completed the most thorough study of factors related to program errors in AFDC.20/ In particular, the study was intended to address two concerns:

- Are there factors beyond the control of State or local administrators and, if so, to what extent do they contribute to error?

- To what extent do State or local administrative procedures affect the rate of error?

Unfortunately, the data used to address these questions were relatively old - QC reviews for 1978 and Census data for 1970. To the extent that current administrative procedures do a better job of controlling errors than those in use in 1978, the reported effects on error rates may not be similar to present relationships.

The analysis proceeded iteratively from case-level analysis to an analysis of local agency influences to the effect of State administrative procedures. Each stage is described below:

- Case-level analysis examined the effects on error of individual case characteristics including demographic features of the assistance unit (case composition, deprivation factors, and presence of earnings), how long the case had been receiving assistance, and how much time had elapsed since the most recent action on the case.

- Local-level analysis examined the effect of socioeconomic conditions (i.e., per capita income, crime rate, population density, unemployment rate, residential mobility, adult female education, non-English language, and residence in one of the thirty largest cities as measured by population) and administrative policies (e.g., use of different verification procedures, automation, wage-matching, caseload size, monthly reporting) on error rates.

20/Ault, Thomas, Sally Davis, Gregory Mills, and Phillip Steitz, AFDC Quality Control Study: Analysis of Payment Error in Aid to Families with Dependent Children (2 vols.), February 1986.

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- State-level analysis examined the effect on error rates of State program policies, administrative procedures, and QC practices including: Federal share of benefits, consolidation of shelter costs, availability of AFDC-U, asset limit, time spent per QC review, etc.

Each type of analysis examined five different types of error: ineligibility/overpayment, underpayment, agency error, non-technical error (i.e., excluding errors related to non-adherence to procedural rules such as WIN registration), and income error.

The primary analytical technique used was ordinary least squares (OLS) regression. Two sets of analyses were performed: one focusing on the incidence of each type of error, and one focusing on the amount of error for cases having recorded errors. The analysis was performed in three phases. First the "case-level" analysis examined the effect of case characteristics on payment error, seeking to explain the variation in case-level error within local welfare agencies. The second phase, the "local-level" analysis, examined the variation in payment error observed among local agencies but within States, using the findings of the case-level analysis to adjust local agency error data to account for differences attributable to case demographic characteristics. The resulting "adjusted error findings" controlled for the effect of both case and State factors. The independent variables in the local-level analysis pertained to local administrative practices and local socioeconomic conditions. The third phase similarly adjusted State error data to control for the amount of interstate variation attributable to differences in case characteristics, local administrative practices, and local socioeconomic conditions to examine whether the remaining interstate variation in error could be explained by differences in State AFDC policies, State administrative practices, and the nature of State quality control review systems.

The findings reported[21] by the authors were:

- Case-, local-, and State-level explanatory variables together explained relatively small amounts of the variation in the error outcome measures examined by the study. The fully specified model explained 9.6% of the

21/Ibid, pp. iv, v, and 13.

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variation in the incidence of "total" ineligibility/overpayment error, 3.5% of underpayment error, 4.3% of agency error, 11.3% of non-technical error, and 16.5% of income error.

- When administratively controllable variables were removed from the model, the percentage of explained variation was reduced slightly, but in each situation by an amount less than two percentage points. When controllable variables were included alone, the models became very weak, explaining less than 1% of the variation in all but the "total" (1.5%) and agency error (1.1%) definitions.

- Each of the following case types was significantly more likely to receive erroneous payments than the average AFDC case: cases overdue for redetermination, cases with earnings, unemployed parent cases, and cases with five or more persons. Note, however, that each of these case types is relatively rare.

- Several administrative procedures effectively limited incorrect payments, especially incorrect payments attributable to misreported income. Particularly effective were procedures that recorded interim changes in client circumstances such as mailed change forms, mandatory monthly reporting, and face-to-face interviews.

  In addition, home visits and employer verification for current earnings during the application and redetermination process showed strong error-reducing effects.

  Finally, several computer applications successfully limited erroneous payments: tickler files to identify cases likely to experience changes in circumstances, data checks for consistency throughout the application and redetermination process, and file matches with other agency files maintained by State and local government agencies to determine accuracy of client data.

- State policy effects proved difficult to estimate through the statistical analysis. Tentative results, however, were that States that paid a higher share of benefit costs and had higher payment standards than average tended to have lower overpayment rates than average. This suggests that States do respond to financial incentives to lower erroneous payments.

- Several socioeconomic factors characteristic of urban environments tended to occur with higher-than-average

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ineligibility/overpayment error, including total population size of the area in which the agency is located, population density, crime rate, and size of agency caseload.

With regard to the particular effect of uncontrollable factors, the authors22/ point out that:

> Viewed together, these findings appear to indicate that factors beyond administrators' control contribute somewhat to error rate levels, but only explain a small percent of them. Even such a tentative conclusion is not entirely warranted for the following reasons. First, as just noted, all variables included in the analysis explained less than 10% of error variation. Because of the low explanatory power of the full model, inferences on the basis of the level of explained variation should be made with caution. Second, the statistical results may be partially attributable to the structure of the data. Nearly all of the controllable variables are measured at the local and State levels, making it impossible for them to contribute significantly to explaining within-office variation, the source of most of the variability observed. Finally, to the extent that either (1) the controllable variables are subject to measurement error or (2) we have not controlled sufficiently for important aspects of the administrative environment, our estimate of the combined effect of the controllable variables is understated.

With the exception of variables specific to the AFDC Program, we have included all of the identified influential caseload and socioeconomic variables in our analysis.

Implications Of Previous Research

Attempts to relate payment errors to case characteristics, local area socioeconomic variables, local agency procedures, and State administrative practices have accounted for very little of the observed variation in error rates. In general, the various models tended to account for 10 percent or less of the variation in incidence and amount of error. To date, therefore, our understanding of the determinants of program errors appears to be quite limited.

22/Ibid, p. 13.

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All of the previous analyses, however, have focused on "static" characteristics. As Budding accurately points out, it may be that variations in error rates are more related to the dynamic nature of the caseload, i.e., the extent to which households enter and leave the program and/or experience changes in their circumstances which subsequently affect their eligibility for benefits. Because of data limitations, we were also unable to capture such factors in our analysis. Consequently, we do not know the extent to which these variables influence error, or the effect of their exclusion on our findings.

Despite the low overall explanatory power of the models examined in the literature, several variables were found to be consistently related to higher error rates:

- the presence of earnings;
- household size;
- receipt of unearned income (particularly SSI, RSDI benefits, and pensions); and
- education level of the head of the household.

In addition, where tested, the following environmental characteristics were found to be significant: population density, urbanicity, crime rate, and local agency caseload size. For the most part, the case-level characteristics are related to the degree to which the household situation is complex to administer, e.g., having various sources of income and being larger in size. The geographic area variables are largely measures of whether the household resides in an urban area.

We have used these results to guide our present analysis, both in the choice of which variables to include in our model and as an indication of the explanatory power we can reasonably expect.

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III. ANALYTIC METHODOLOGY

This chapter presents our approach to developing statistical models to estimate the effect of caseload and socioeconomic characteristics on State payment error rates. It consists of four major sections: (1) the conceptual model that forms the basis of our analysis; (2) the mathematical model used to estimate the effect of these factors including separate discussions of the form of the model, the dependent variables, explanatory variables, data sources, and model specification; (3) procedures for calculating adjusted State error rates using the results of the estimated statistical model; and (4) a discussion of alternative modeling approaches.

Conceptual Model

As discussed in Chapter I, State error rates vary widely, and some have argued that a substantial portion of this variation results from factors outside the States' control, such as the nature of the caseload they must serve, and from external conditions, such as the unemployment rate. Because error rates are used in calculating fiscal liabilities for overissued food stamp benefits, it is also argued that error rates should be adjusted to remove the effect of these external factors. In this manner, States would be held to similar standards of performance. Currently, States with more difficult caseloads are held to higher relative standards since they face the same threshold for establishing fiscal liabilities for overpayment errors.

This argument posits two types of factors which may explain erroneous payments: administratively controllable factors such as length of certification periods, the use of computerized wage matching systems, the ratio of eligibility workers to clients, and eligibility worker training programs; and external factors such as caseload characteristics and socioeconomic conditions such as the local unemployment rate. The basic argument is that these external factors make it more difficult to lower error rates in some States than in others; States can improve their administrative procedures in ways that reduce overpayments, but it is simply more difficult (and more costly) to do so in certain situations. One could, of course, argue that all sources of error are ultimately controllable. However, the cost of doing so may exceed the potential benefits (i.e., reduced overpayments, avoided fiscal liabilities).

In practice, this model of food stamp error is complicated by the fact that we can measure some, but not all, of the factors which affect error rates. A few examples illustrate these categories. A State-mandated ratio of food stamp supervisors

could create an administrative system which combined the typical procedures used by the States in all aspects of the program, we would create the average administrative process. Second, the extent to which each State is better or worse than average is related to each State's administrative competence. We denote this "competency factor" as CF_i; it can be either negative (below average and leading to a higher error rate) or positive (above average and leading to a lower error rate). We can, then, re-express Equation (2) to capture the effect of differing State competencies:

$$PER_i = E_u - (AAE + CF_i) \qquad (3)$$

Under this formulation, we explicitly recognize differing commitment, and ability, to control error. The competency factor for an individual State can make its error rate either higher or lower than the average, depending upon where it falls in the range of administrative excellence.

But are observed differences in payment error rates completely attributable to differences in the level of administrative competence? Some have argued that the answer is no; not all States face the same sorts of problems. These external factors include such things as the types of clients they have to deal with (certain households have more complex situations), local unemployment conditions, and different attitudes toward welfare programs in general. Because States differ on factors which are beyond their control and which may increase the likelihood of error, even if they were all equally competent, there would still be differences in observed error rates. The world is not homogeneous; even in the absence of any administrative procedure to reduce error, States would differ in the overpayments they would make. This formulation leads to the following:

$$PER_i = (\sum_j EF_{ij}) - (AAE + CF_i) \qquad (4)$$

The second term in parentheses $(AAE + CF_i)$ represents everything that the State does to control payment errors. Given the circumstances they face, it is their "best shot" at reducing mispayments. The first term, $\sum EF_{ij}$, represents the effect of the State's unique circumstances. The EF are the effects of external factors which can cause errors; these include any characteristics which the State cannot choose under the existing rules of the program. For example, a State cannot choose how many households with earnings will apply for

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benefits. This factor is outside its control; all the State can control is the extent to which it ensures that only households which meet the eligibility requirements receive benefits (for example, by employing computer matching to verify earnings). These external conditions, taken together, establish the upper-bound error rate we would expect to observe in the absence of State administrative action.

As depicted in Equation (4), a large number of such external factors can affect errors (hence the use of the "j" subscript). Some tend to increase errors, and others tend to reduce errors. When the external factors' effects are summed, they produce the "state of the world" which must be faced when developing an administrative system. In other words, if all States faced the same circumstances, we would expect $\sum EF$ to be constant across States. But since States are not the same, they face different problems which are reflected in the different constellations of external factors which characterize their caseloads.

However, this is not the end of the story. As we have expressed our model, the level of a State's competence (CF_i) and the external factors (EF_j) have separate effects on error rates. That is, the model in Equation (4) hypothesizes that States achieve some general level of competence in the way they administer the program, independent of the difficulty of the situation that confronts them. This is probably <u>not</u> an adequate representation of the way States actually operate. It is more likely that States introduce controls in response to the problems they face. As the GAO23/ pointed out, the argument over whether to adjust State error rates assumes that "... distinctions can be made between two kinds of payment errors: those caused by factors outside a State's control and those caused by poor program management. This may not be possible. It is unclear which fraction of earned income errors is due to the number of wage earners in a caseload, and which to agencies' failure to properly verify wage income."

23/U.S. General Accounting Office, <u>Managing Welfare: Issues and Alternatives for Reforming Quality Control Systems</u>, August 1986, p. 44.

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As a result, there is an interaction between the State's competency factor and the constellation of external factors present in the respective States:

$$PER_i = (\sum_j EF_{ij}) - (AAE + CF_i) + \sum_j CF_i \times EF_{ij} \qquad (5)$$

Now the first term in parentheses represents the "pure" effect of the external factors on the State's error rate, i.e., before taking into account the State's efforts to control errors attributable to the existence of particularly difficult situations. The next term is the State's controllable actions to reduce error (e.g., short certification periods, computer matching, automated systems). Finally, the last term captures two aspects of the hypothesized interaction effect: States vary in how well they deal with specific types of external factors (e.g., if a State has a large number of wage earners, it is more likely to use a computer wage-matching system), and States with very difficult situations (i.e., well above average on a particular factor) will get a larger payoff (i.e., a larger reduction in their error rate) for gains they make toward controlling that specific type of problem.

To better explicate this model, we consider two States, S_1 and S_2, which face similar external circumstances. In the absence of any administrative actions to reduce errors, we would expect each State's payment error rate to be equal to 35 percent (i.e., the upper-bound error rate). Further, assume that the two States differ with respect to their ability to control errors due to one external factor EF, that the average administrative effect is equal to 30 percent, and that the two States have the following administrative characteristics:

S_1: CF_1 = -3 (i.e., its general competence is worse than average);

$CF_1 \times EF_1$ = +2 (i.e., its ability to deal with the particular factor is also worse than average);

S_2: CF_2 = +1 (i.e., its general competence is better than average)

$CF_2 \times EF_1$ = -1 (i.e., its ability to deal with the particular factor is also better than average).

We would, then, observe the following error rates for the two States:

$$PER_1 = (35) - (30 - 3) + 2 = 35 - 27 + 2 = 10\%$$

$$PER_2 = (35) - (30 + 1) - 1 = 35 - 31 - 1 = 3\%$$

State S_2, because of its superior ability to deal with a particularly difficult situation, is able to achieve a lower error rate than State S_1, even though they are equivalent in all other respects.

With this conceptual model in mind, the next section describes our attempt to estimate a model that tests whether caseload and socioeconomic characteristics lead to variation in error rates over and above State efforts to control error.

A Mathematical Model

This section consists of five parts: a discussion of the form of the model used in this analysis; the nature of the dependent variables; the explanatory variables used; data sources; and efforts to specify the model.

The Form of the Model: In order to answer the question "Do caseload and socioeconomic characteristics make a difference?" we need to construct a model very much like equation (5) above (with the addition of a random fluctuation term, of course, because we will be using sample data). That is, we need a model which distinguishes between States' actions to control error and external factors which make their job more or less difficult.

As discussed in Chapter I, the QC system ordinarily reports dollar error rates, which are equal to the percentage of total benefits that are erroneous payments. Therefore, the reported error rate for a State is defined as:

$$PER_i = \frac{E_i}{A_i} \times 100 \qquad (6)$$

where:

PER_i = the State's payment error rate;

E_i = total dollars paid in error (overpaid or paid to ineligibles in the period); and

A_i = total allotments in the period.

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One important feature of this measure is that it expresses error dollars relative to dollars paid, not dollars that should have been paid. When a State makes a payment error, it is added to both the numerator (E_i) and the denominator (A_i); as a result, a State's error rate is affected not only by the amount of overpayments it makes, but also by the size of its average food stamp allotment. Moreover, both quantities vary from State to State as a result of differences in both administrative procedures and caseload characteristics and socioeconomic conditions. For example, having more large households to deal with may increase the likelihood of error, but this also increases the size of the average food stamp allotment. This point has, however, been largely ignored in prior research. For this study, we have incorporated this relationship by adjusting both the numerator and the denominator of equation (6) for the effect of caseload and socioeconomic factors.

To continue, recall that overpayment errors are of two types--overpayments to eligible households and payments to ineligible households. Because payments to ineligible cases are generally larger than overpayments to eligibiles (see Exhibit 3.1), States with greater numbers of ineligibles will, other things being equal, have larger payment errors than States with fewer such cases. Moreover, it is reasonable to believe that separate processes lead to these two types of payment errors. For example, reporting errors related to assets affect a household's eligibility for benefits but not the size of the allotment. As a consequence, it is useful to decompose a State's payment error rate into the following parts:

$$PER_i = \frac{E_O + E_I}{A} \times 100 \qquad (7)$$

where E_O and E_I are the total dollar error amounts for overpayment errors and ineligibility errors, respectively.

Each type of error (overpayment errors and ineligibility errors) can be further decomposed into two components: the probability that a case will have an error (this is simply the case error rate or the mean of a variable whose value is "0" for correctly-paid cases and "1" for cases in error) and the amount of the overpayment, given that an error has occurred. Maintaining our distinction between the two types of errors, we can then re-express Equation (7) in the following form:

$$PER_i = \frac{I_O \bar{e}_O + I_I \bar{e}_I}{\bar{A}} \times 100 \qquad (8)$$

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EXHIBIT 3.1
Distribution of Overpayment Errors by Whether Case Is Eligible or Ineligible for Benefits

Amount of Overpayment Error	Overpayments to Eligible Cases (%)	Payments to Ineligible Cases (%)
Under $10	13.6	0.5
$10 - $49	56.4	27.0
$50 - $99	20.5	29.0
$100 - $149	6.5	21.9
$150 and Over	3.0	21.6

Source: Integrated Quality Control System data for Fiscal Year 1984.

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where I_O is the incidence (or probability) of overpayment error, I_I is the incidence of ineligibility error, and $\bar{e}_O$ and $\bar{e}_I$ are, respectively, the average overpayments for only overpayment error cases and only ineligibility cases.

Therefore, to adjust a State's error rate for the effect of external factors, we need to examine their influence on each of the five components of Equation (8). That is, we require separate models for:

1) $Prob(i_O=1)$ = The probability that an overpayment error will occur (i.e., I_O).

2) $E(e_O|i_O=1)$ = The expected value of an overpayment error, given that such an error has occurred (i.e., the mean $\bar{e}_O$).

3) $Prob(i_I=1)$ = The probability that an ineligibility error will occur (i.e., I_I).

4) $E(e_I|i_I=1)$ = The expected value of an ineligibility error, given that such an error has occurred (i.e., the mean $\bar{e}_I$).

5) $E(A)$ = The expected value of the benefit payment (i.e., the mean $\bar{A}$).

In each model, the unit of analysis is the individual food stamp case. The premise of adjusting for external factors is that a State's errors are influenced by conditions that State-level food stamp managers cannot be expected to control, most importantly the characteristics of the caseload and the socioeconomic conditions which confront them. For each model, then, we could consider two categories of explanatory variables:

EF = the external factors that influence errors, such as caseload composition or local socioeconomic conditions;

CF = controllable factors influencing errors, such as the policies and procedures by which the State administers the program.

For the purposes of this analysis, however, we have chosen to explicitly measure only external factors and to capture everything that States do to control error by the use of a

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State "indicator variable," which is equal to "1" if a case is in that State and is equal to "0" otherwise. This approach was taken for several reasons. First, data on local administrative practices are not available in a way that can be linked to case-level information. Second, even if some data were available, it is unlikely that we could adequately capture the total effect of local agency actions to reduce overpayments. Third, if we added some State-level explanatory variables to our model, we would have to remove an equal number of State indicator variables24/ and try to obtain data on all State procedures which could be expected to control errors--as with the local agency data, a highly unlikely prospect. The use of the State indicator variables, therefore, allows us to represent State responses to the characteristics of their caseloads (both measurable and unmeasurable) without having to resort to incomplete measures of administrative practices. Statistically, the indicator variables completely capture all of the inter-State variation on those factors not included in the model.

In order to see better how this works, consider the model which describes variation in the amount of State overpayment errors:

$$y_{ij} = \alpha_i + \beta X_{ij} + u_{ij} \qquad (9)$$

where y_{ij} is the overpayment amount for case j in State i, β is the vector of regression coefficients for the caseload and socioeconomic characteristics, X_{ij} is the vector of values of these same characteristics for case j in State i, α_i is a constant for State i (the coefficient of that State's indicator variable), and the u_{ij} are random fluctuations.

If we measure each case's values on the characteristics included in the model as deviations from the national mean25/, we can interpret the resulting regression parameters in the following manner:

24/One cannot add State-level variables to a model that already contains an indicator variable for each State, because the model (or, more precisely, the matrix of observations on the explanatory variables) would then be singular.

25/That is, for each variable we subtracted the value of the overall weighted mean.

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- The β coefficients on the caseload and socioeconomic characteristics represent the change in the overpayment amount we would expect to find for a unit change in the corresponding factor (after allowing for simultaneous straight-line changes in all the other variables in the model). In other words, it represents the extra (or lesser) amount of error that results from cases with this particular condition (e.g., presence of earnings).

- The α_i represent the State average overpayment amounts, adjusting for differences in the included caseload and socioeconomic characteristics. That is, α_i is the average overpayment State i would have made if it had a caseload which resembled the national average on the external factors included in the model.

In this formulation, the coefficients on the individual caseload and socioeconomic characteristics (β) do not, as discussed earlier, represent the "pure" effect of that condition on the dependent variable. Rather, they represent the extra amount of error that comes from the general difficulty of dealing with such cases and the average26/ of all States' competence in dealing with problems of this type.27/

26/Because our data consist of samples of different sizes drawn from each State's caseload (where the sample size is not proportional to the size of the total caseload), the average is weighted by the size of each State's sample. The estimated effect of a particular caseload characteristic (e.g., presence of earnings), therefore, will be influenced more heavily by States with larger QC samples (e.g., Wisconsin with 3,000 cases vs. Nevada with 300 cases). This issue is discussed at the end of this section.

27/We have not estimated models which explicitly consider the types of interaction effects we presented earlier in our disussion of a conceptual model. To do so would greatly increase the size of the equations to be solved. For a model with four caseload characteristics, to include interactions for each term would expand the model from 54 variables (50 State indicators plus the 4 characteristics) to 254 variables.

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Take, for example, a model consisting of one external factor x, (such as the amount of a household's earned income) and two State indicator variables S_1 and S_2. This would yield the following equation:

$$y_{ij} = \beta(x_{ij} - \bar{X}) + \alpha_1 S_1 + \alpha_2 S_2 + u_{ij} \qquad (10)$$

For case j in State 1, then

$$L_1: y_{1j} = \beta(x_{1j} - \bar{X}) + \alpha_1 + u_{1j}$$

and for case j in State 2

$$L_2: y_{2j} = \beta(x_{2j} - \bar{X}) + \alpha_2 + u_{2j}$$

Geometrically, we have the situation depicted in Exhibit 3.2. The relationship between overpayments and x is the <u>same</u> for both States; i.e., the slope of the line is the same in both instances. L_1 applies when $S_1 = 1$, and L_2 applies when $S_2 = 1$. The two lines are not independently fitted to the data; rather two lines are projected from Equation (10), one corresponding to the data from State 1 and one corresponding to the data from State 2. The points "a" and "b" are the <u>unadjusted</u> means for State 1 and State 2, respectively; the points a' and b' are the respective <u>adjusted</u> means. The adjustments reflect the fact that the two States differ, on average, with respect to the characteristic x. The difference between the adjusted and unadjusted means is the change one would expect to see in the outcome measure, y, if each State had a caseload that was like the national average on x.

Before moving to the next topic, two aspects of the selected statistical model warrant discussion. First, we have opted to fit a single equation to explain variation in each of our five dependent measures rather than developing separate models for each State. Although the use of separate State models would have allowed us to examine more carefully the possible interactions between State administrative practices and the effect of external factors, this approach is judged unacceptable from one important perspective. The notion of adjusting error rates for caseload characteristics argues for the assumption that a single underlying process produces errors; i.e., having a relatively large proportion of cases with error-prone characteristics will increase the likelihood of error regardless of the State in which it occurs. Therefore, we want an adjustment procedure which holds the relationship between characteristics and error constant and allows adjustments only to the extent that States vary on the individual factors.

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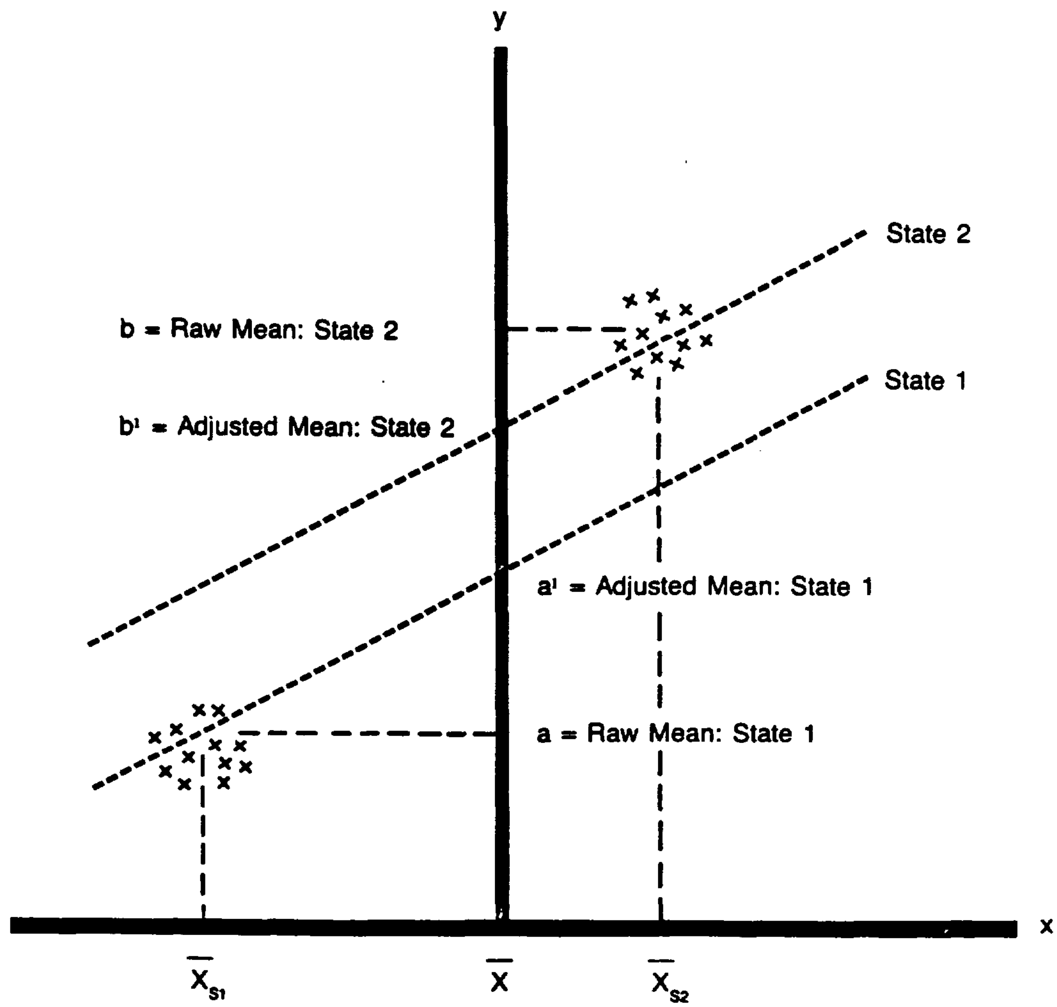
EXHIBIT 3.2
Diagrammatic Explanation of Statistical Model



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Second, we considered but decided against estimating the models using a weighted regression technique. Many States separate their caseload into strata for the purposes of the QC system and assemble their QC samples by drawing a simple random sample within each stratum. For example, some States stratify according to whether the food stamp case also receives AFDC; others treat cases that are active during calendar periods of six months, three months, or even one month as separate strata. To compensate for the fact that samples usually constitute different fractions of the caseload in the strata, each case in the QC sample receives a weight. These weights allow each case in the stratified sample to represent the same number of cases in the overall caseload.

In the usual stratified sample one constructs the weighted mean $\bar{y}_{st}$ as follows. Let

N_h = number of cases in the caseload of stratum h;

N = total size of caseload = $\sum N_h$;

n_h = size of sample in stratum h; and

$\bar{y}_h$ = sample mean in stratum h.

Then the estimate of the population mean based on the strata is,

$$\bar{y}_{st} = \frac{\sum N_h \bar{y}_h}{N}$$

In terms of the individual observations y_{hi}, we may rewrite this formula, summing over strata and over observations within strata, as

$$\bar{y}_{st} = \sum_h \sum_i w_{hi}\, y_{hi}, \text{ where } w_{hi} = N_n/(n_h N);$$

that is, each observation in stratum h receives the same weight, and that weight is inversely proportional to the sample size in that stratum and directly proportional to that stratum's fraction of the full caseload.

It is straightforward to use these weights (which can be derived from information supplementary to the IQCS data base) in calculating overall national means according to the formula above. For example, as noted earlier, we centered each of our explanatory variables at its weighted national mean.

One might expect the same weights to be suitable for use in a weighted-least-squares regression, as part of the process of determining adjusted State error rates. However, the use of weights in regression analyses based on stratified samples involves several complications that have generated considerable discussion in the statistical literature. If the regression coefficients can reasonably be regarded as the same for all States (as discussed above), then it is not necessary to use weighted regression. In fact, weighting is undesirable, because it introduces a bias of unknown extent, as DuMouchel and Duncan28/ demonstrate. As an alternative model, one could consider separate, potentially different, sets of regression coefficients in the strata and decide to estimate the weighted average regression coefficient, which combines these within-stratum coefficients according to weights that reflect the respective contributions of the strata. Unfortunately, as DuMouchel and Duncan also show, weighted-least-squares regression does not provide an unbiased estimate of the weighted average regression coefficient, either. Again, the bias cannot be determined from the data. Furthermore, one cannot determine which of the two biases is actually smaller. For these reasons we used ordinary (unweighted) least-squares regression in this analysis.

The Dependent Variables: As described earlier, this analysis involved three types of dependent variables: an indicator variable, equal to "1" if the case had an overpayment or ineligibility error and "0" if the case was correct (which included underpayments); the dollar amount of the overpayment or ineligibility error29/; and the amount of the household's total food stamp benefit.

With regard to the amount of an overpayment or ineligibility error (see Exhibit 3.3), an examination of the data suggested

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28/DuMouchel, William H. and Greg J. Duncan, "Using Sample Survey Weights in Multiple Regression Analyses of Stratified Samples," Journal of the American Statistical Association, 78, 1983, 535-543.

29/Because the QC system disregards errors of $5.00 or less, the lowest observed value for this variable is $6.00.

EXHIBIT 3.3: Distribution of Overpayment Error by State

State[a]	Minimum	Lower Quartile (Q_1)	Median	Upper Quartile (Q_3)	Maximum	Q_3-Q_1	N
Alabama	6	16	32	72	301	56	437
Alaska	7	36	76	169	475	133	50
Arizona	6	19	45	94	362	75	503
Arkansas	6	14	37	79	457	65	219
California	6	17	38	74	349	57	247
Colorado	6	21	40	94	301	73	311
Connecticut	6	16	34	64	312	48	156
Delaware	6	17	41	78	199	61	54
District of Columbia	6	19	47	80	377	61	107
Florida	6	16	36	84	319	68	384
Georgia	6	16	36	82	593	66	249
Hawaii	6	16	42	107	474	91	81
Idaho	6	15	36	78	253	63	98
Indiana	6	17	43	88	571	71	318
Iowa	6	13	35	72	253	59	209
Kansas	6	14	30	72	361	58	151
Kentucky	6	17	43	83	370	66	362
Louisiana	6	19	49	107	514	88	214
Maine	6	12	29	76	301	64	136
Maryland	6	18	37	77	223	59	169
Massachusetts	6	20	46	94	252	74	200
Michigan	6	14	33	74	316	60	313
Minnesota	6	15	31	67	301	52	208
Mississippi	6	14	30	76	337	62	247
Missouri	6	12	29	61	278	49	401
Montana	6	16	39	76	233	60	136
Nebraska	6	16	38	78	333	62	187
Nevada	6	10	42	127	247	117	17
New Hampshire	6	21	51	76	242	55	77
New Jersey	6	18	39	76	301	58	346
New Mexico	6	17	42	96	380	79	392
New York	6	15	38	84	254	69	225
North Carolina	6	15	34	68	250	53	149
North Dakota	6	16	37	93	313	77	39
Ohio	6	18	37	76	350	58	384
Oklahoma	6	16	33	62	361	46	182
Oregon	6	16	41	76	319	60	140
Pennsylvania	6	14	32	76	340	62	236
Rhode Island	6	16	33	65	253	49	172
South Carolina	6	16	36	75	337	59	346
South Dakota	6	13	29	48	204	35	68
Tennessee	6	15	33	63	253	48	171
Texas	6	16	36	76	399	60	195
Utah	6	23	48	106	319	84	97
Vermont	6	15	38	71	345	56	121
Virginia	6	14	33	73	443	59	148
Washington	6	18	39	70	412	52	391
West Virginia	6	16	33	69	347	53	186
Wisconsin	6	18	38	75	291	57	442
Wyoming	6	18	46	109	253	91	56
Guam	8	14	53	115	473	101	44
Virgin Islands	7	23	57	103	385	81	89

[a]Excludes Illinois, which was involved in a demonstration project during FY 84.

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The first four categories apply to individual recipient households, whereas the last category contains socioeconomic characteristics of the local geographic area in which the household resides. Appendix C provides a list of the specific variables that were examined for possible inclusion in the statistical models.

These variables do not "cause" errors. Rather, the presence or absence of these factors is hypothesized to be related to some (unknown) process which gives rise to errors. For example, the presence of multiple sources of earned income, or simply the size of the household may make the determination of eligibility more complex (or be associated with an increased probability of subsequent changes in circumstances which alter eligibility) and, as a result, increase the likelihood of mispayment. Other factors, such as the age and citizenship of the head of household, may be related to the ability to understand and comply with program regulations, instructions and requirements.

Finally, the social environment variables may be related to error rates in several ways. First, they may serve as a proxy for the previously discussed categories (e.g., case complexity). For example, a low unemployment rate may increase the chance that more people in the case have earnings. Second, social environment variables may affect client attitudes--for example, a high poverty rate or a high crime rate may be associated with cynicism or even antipathy toward institutional rules such as Food Stamp Program regulations. Third, social environment variables may identify geographic areas where a large number of social problems converge and place a particularly heavy burden on the welfare system, creating an "overload" atmosphere among eligibility workers.

To be specific, let us examine each of our five statistical models and see which variables we would expect to affect the dependent variable. Starting with the allotment amount, it is important first to keep in mind that average food stamp allotments include both erroneous and correct payments. Hence, a State that makes more errors will have a higher average allotment, other things being equal. Beyond this, we would expect three types of factors to influence allotment amounts:

- Program rules. Although most rules regarding food stamp eligibility and benefit amounts are constant across States, exceptions exist. For example, the standard monthly

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utility allowances vary from State to State. Alaska, Hawaii, Guam and the Virgin Islands have higher income eligibility limits and a higher thrifty food plan than the contiguous 48 States.

- Caseload composition. Eligibility and benefit amounts are based on reported household characteristics such as household size, income and deductions. Hence, variation in these characteristics across States causes variation in average allotment amount.

- Other assistance programs. Food stamp allotments are reduced when a household receives income from AFDC, GA, and other assistance programs. State-to-State differences in the existence of such programs (especially GA) or the amount of benefits they pay (especially the AFDC needs and payment standards) influence the number of food stamp households receiving such benefits and the amount of benefits they receive, and hence affect the average food stamp allotment.

For our purposes, we need to determine whether to adjust State error rates for the effect of these three possible sources of variation. Where program rule differences are allowed to vary from State to State (e.g., the treatment of standard utility allowances), we should not adjust the State means for this source of variation. On the other hand, differences in caseload or socioeconomic characteristics should be used to adjust State means.30/ The final area, other assistance programs, is not so clear-cut a decision. If we consider them to be outside the control of Food Stamp Program managers, their effect is like that of household characteristics and should be used to adjust State means. If we consider them controllable factors, their effect is like that of program rules, and they should not be used to adjust State means. Either treatment could be considered appropriate -- it represents a policy decision rather than a technical decision. For this analysis, we have assumed that variations in other assistance programs are external to the administration of the Food Stamp Program and have explicitly included them in our models.

30/We have to be careful, however, not to include program rule differences as an explanatory variable (such as using excess shelter deductions, which includes the effect of utility allowance variation).

The incidence of overpayment error is the result of a QC reviewer discovering more earned or unearned income than was in the case record, more deductions than should have been taken, a person included in the case who should not have been, or an arithmetic error. The types of factors we would expect to influence the incidence of error include:

- Definitional Factors: We would expect factors such as the presence and amount of various kinds of income (earned and unearned), the presence and amount of deductions, and household size to be good predictors in this model. Errors in these factors will, by definition, lead to an overpayment error.

- Case Complexity: The greater the number of opportunities to make a mistake, the greater the likelihood of an error. Elements of such complexity include the number of people in the household with earnings or other types of income, the number of different types of deductions, the total number of persons (or adults) in the case, and the number of program elements that must be considered by the eligibility workers.

- Factors Contributing to Client Error: Errors can occur either from a deliberate motivation for gain or from ignorance or confusion. Factors related to such errors include aged or disabled head of household, citizenship (a proxy for language) and area measures such as the proportion of the population that are non-English speakers and the proportion with less than high school education.

- General Environmental Factors: It is hypothesized that offices located in inner-city neighborhoods are characterized by conditions which quickly overload eligibility workers and make it hard to get information and handle it correctly. At the other end of the spectrum is the rural office, where the pace is slower and the workers often know the client's family and employer. Possible predictors here, all measured at the area level, include: residing in a major city, total population, population density, percent of population below the poverty level, and crime rate.

- Changing Circumstances: A change in household circumstances (e.g., income, employment status, deductions, household size), if not reported, can cause an overpayment

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error. One can hypothesize a number of possible predictors of this phenomenon, such as: previous earnings history, whether the household owns or rents (costs probably change less for owners), length of time the case has continuously been receiving assistance ("long term" cases are probably less likely to experience changes), the number of persons (other than the head) between the ages of 16 and 25 (who are most likely to leave home), the number of children under age 7 (could change child care deductions), the number of persons aged 62-65 (most likely to start getting Social Security), the number of persons aged 16-18 (likely to change status), and area measures such as the unemployment rate and the percent employed in agriculture (more seasonal jobs).

A difficulty that does arise with regard to the participant-level data is related to the use of either "true" or "reported" (at the time the household applies for benefits) values for these factors. Because we are trying to distinguish between cases that have errors and those that are correct, we would like to know the true circumstances of the error cases (presumably, the reported information is the same as the true information for the correct cases). The fundamental reason that error cases have errors is that their true circumstances are <u>not</u> the same as their reported circumstances. But the available data on true circumstances (see next section) are quite limited. For example, although we can determine whether a household truly had earnings and did not report them, we cannot determine the <u>amount</u> of the unreported income. Consequently, although we have tried to use true measures, we are unable to do so for all the possible influential factors and must resort to the use of reported information.

With regard to the <u>amount of an overpayment error</u>, its magnitude depends on the kind and size of error that is made. Inclusion of ineligible persons results in an error that is essentially some constant (about $50) times the number of ineligibles included, unless that person accounted for some reported income or expenses. Similarly, undercounting income or overcounting deductions results in error equal to a predictable amount. <u>A priori</u> we would expect that factors that make such errors more likely to occur will also tend to make them larger. Therefore, most or all of the factors cited in discussing the incidence of overpayment error could be predictors for the amount of the error.

The incidence of ineligibility error depends upon the QC reviewer finding enough previously unknown income to put the case over the income eligibility limits (given its household size, etc.), or enough ineligible people in the case that the benefit amount falls below 30 percent of net income, or enough unknown resources to put the case over the asset limit. With the exception of the resources, then, an ineligibility error should be produced by the same factors that would lead to an overpayment error. The only distinction lies in whether the amount of income, deductions, or household size that the QC reviewer finds is enough to take the case over the eligibility limit. We would, therefore, expect the same variables to be good predictors in this model with the addition of resource variables.

Finally, with regard to the amount of an ineligibility error, when a case is determined to be ineligible, the magnitude of the error is, by definition, simply its benefit amount. Therefore, the same factors that determine the size of a household's benefit should influence the amount of an ineligibility error, if one occurs.

In contructing our statistical models, we have used these hypothesized relationships to guide our specification decisions. As will be discussed below, this analysis was an exploratory effort; to the extent possible we tried to use our theoretical understanding of the payment error process and past research to guide our development of an adjustment procedure.

As a final note, the reader should keep in mind that the variables used in this analysis represent only static characteristics which may affect error rates. Dynamic factors such as changes in individual household circumstances, the extent to which individual households enter (or leave) the program, growth in caseload size, and the volatility of local labor markets are not measured in this analysis. Although we were unable to test the effect of these factors, it is certainly possible that they have an influence on payment errors. For example, errors may increase if there are changes that overwhelm existing systems and increase the likelihood of mistakes or things "slipping through the cracks." At a minimum, the reader should keep this point in mind when reviewing the findings presented in the following chapters, especially because, as will be discussed in Chapter V, the adjustment models are quite sensitive to the exclusion of key explanatory variables.

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Data Sources: This analysis draws on two primary data sources: Integrated Quality Control System (IQCS) data for case-level information and Census Bureau data for area socioeconomic characteristics. FY 1984 IQCS data were used to build the statistical models, which were later tested for stability using the FY 1985 IQCS data.

The QC review data are derived from the Food Stamp Program quality control system described in Chapter I. Cases are part of independent random samples drawn from the total caseload in each State. In some States, cases are stratified prior to the selection of the QC samples. For each selected case, reviewers complete a review data sheet (see Appendix A) documenting the results of an independent verification of eligibility for benefits. The minimum annual sample size in a State varies, but not proportionately, with the size of the State's caseload, from 300 to 2,400 cases. In all, 64,343 cases were available for analysis in the 1984 file, and 69,017 cases in the 1985 file.

The data collected as part of the QC review are summarized and submitted by the States to FNS. The data available on each case include the following:

- Identifying information: case and review numbers, local agency codes, review date, and stratum (if the State's sample is stratified).

- Summary of review findings: eligibility determination (correct, underpaid, overpaid, ineligible) and the amount of any error (if over $5.00, as mentioned earlier).

- Case information: date of most recent application; date and type of most recent action; number of case members; total value of liquid assets, real property, vehicles and other non-liquid assets; identification of party responsible for case processing; months in certification period; amount of the food stamp allotment; use of expedited service or an authorized representative; gross and net income; and amounts of each of the allowed income disregards (e.g., shelter costs).

- Detailed person-level information: for each adult person in the household: case affiliation (member of case under review or not); relationship to head of household; age; sex; race; citizenship status; work registration status; employment status; and earned and unearned income by source.

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- Detailed error findings: for each error that is found, the element found to be incorrect; the nature of the error; the source of the error (agency or client); and how the error was discovered and verified.

The primary source of data for the socioeconomic variables was the 1980 Census of Population and Housing31/ (Summary Tape File 3A provided summaries by county and place, and Tape File 3B provided summary data by postal zip code). For some variables (e.g., crime statistics), these data were augmented with county summary information from the County and City Data Book.

The Census data were matched to the individual case-level records obtained from the IQCS by the following procedure:

1. Local agency codes were used as the primary link to the Census data.

2. If the local Agency was the only one located within a particular Census county (or a set of multiple counties), then the local Agency code was matched with the appropriate Census county identifiers.

3. If the local Agency was not the only one in a Census county, then the link was made using Census identifiers for minor civil divisions (i.e., cities and towns), "places" with populations in excess of 10,000, or zip codes. The latter were used only where the local Agency's boundaries were smaller than the Census Bureau's designations for civil divisions or places (e.g., within-city offices).

The Census information used in this analysis included the following:

- Total population.

31/U.S. Department of Commerce, Bureau of the Census, Census of Population and Housing, 1980: Summary Tape File 3, Technical Documentation, Washington, D.C., 1982.

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- Urbanicity, total persons per square mile of land area and whether household resides within one of the 30 largest cities32/ (as measured by total population).
- Racial composition, percent of the population that are black, and the percent that are of Hispanic origin.
- Household composition, percent of persons that are in households defined as "family" units and the percent of households that are headed by a female.
- Birth rate, births per 1,000 resident population.
- Housing, percent of year-round housing units that are vacant and median gross rent for renter-occupied housing units.
- Education, percent of population 25 years of age and over having 12 or more years of education.
- Unemployment rate for 1982, percent of the civilian labor force that is unemployed (Bureau of Labor Statistics).
- Occupation, percent of civilian labor force employed in agriculture, and the percent employed in manufacturing.
- Median family income for 1979.
- Poverty status, percent of persons with incomes below the 1979 OMB poverty level.
- Crime, 1981 overall crime rate (per 100,000 resident population) and rate for violent crimes from the Uniform Crime Report compiled by the Federal Bureau of Investigation.

32/Includes, in descending order of size: New York, Chicago, Los Angeles, Philadephia, Houston, Detroit, Dallas, San Diego, Phoenix, Baltimore, San Antonio, Indianapolis, San Francisco, Memphis, Washington, D.C., Milwaukee, San Jose, Cleveland, Columbus, Boston, New Orleans, Jacksonville, Seattle, Denver, Nashville-Davidson, St. Louis, Kansas City, El Paso, Atlanta and Pittsburgh.

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Unfortunately, Census data were not available for Guam and the Virgin Islands. In a few instances we were unable to obtain the information needed to link local office codes to Census identifiers. With the exception of Vermont, the number of cases deleted for each of the remaining 50 States, however, was minimal (a total of only 372 cases).33/

Model Specification: As noted earlier, our research objective is twofold: to examine whether it is possible to attribute variation in payment error rates to caseload and socioeconomic characteristics; and, if so, to develop models which could "adjust" State error rates to remove the effect of State-to-State differences in such factors, i.e., to estimate what a State's error rate would be if it had characteristics like the national average. As with any models of this type, three criteria are important regarding their specification:

1. The models should be as parsimonious as possible. That is, we want the models to have the smallest reasonable number of predictor variables. This produces a model that is most understandable.

2. Variables included in the model would have to be the "best" predictors. Here, best was judged by both the variable's statistical significance in the model (i.e., the magnitude of the t-statistic) and the overall explanatory power of the model (i.e., as measured by the value of R^2).

3. A variable included in a particular model had to "make sense." In exploratory analysis such as this, it is easy just to let the data decide the structure of the models (e.g., using stepwise regression to pick the best combination of variables). We have avoided this latter approach because it can produce results that are not understandable to people who know the program. If these models are to ever be used for policymaking, they must

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33/The numbers per State are as follows: Arizona 7, Colorado 31, Connecticut 2, Delaware 7, District of Columbia 40, Georgia 1, Idaho 6, Kentucky 1, Massachusetts 5, Michigan 1, Nebraska 7, Nevada 15, New York 73, North Carolina 17, Pennsylvania 1, South Carolina 18, Texas 1, Vermont 126, Virginia 1, Washington 2, and Wyoming 10.

reflect relationships that are sensible to managers. Only in this manner would the adjustment process ever be transparent to those who have the most to lose as a result of the changes.

Model development was done using randomly drawn samples rather than the full data set, both for resource considerations and to permit later validation of the models on the remaining cases. For the models of the incidence of error and the food stamp allotment, a 10 percent sample of all cases was used. For the two error amount models, a 20 percent sample of error cases was used in order to provide enough observations for analysis. Final models have been estimated on the full QC sample.

For the model of food stamp allotment, we did not test many alternative specifications. We viewed this as a definitional relationship (as discussed earlier) and only examined different measures of the factors used to compute benefit amounts (e.g., different measures of earned income). For the remaining four models, the following strategy was used:

- Alternative specifications of the models were tested, and regression diagnostics were used to examine possible collinearity among the variables. Initial decisions to include or exclude particular variables were based, as noted above, on the significance of the estimated coefficients (variables were often tested in various combinations). The criterion used to judge statistical significance involved a Bonferroni adjustment for simultaneous statistical tests.34/ Although a rather stringent test, it does prevent the inclusion of marginally adequate predictors.

34/The usual criterion for judging statistical significance is that the observed difference from the assumed null value have no more than a 5 percent probability of occurring by chance. However, when it is necessary to test the significance of two or more estimates simultaneously (as with the more than 50 coefficients in our models) we must give more attention to how we will manage the contribution of chance associated with the multiplicity of estimates. It is not satisfactory to apply an individual 5 percent significance level separately to each estimate; if chance alone were operating, about 92 percent of the time, one or more of the individual tests would indicate a "significant" result, even though there were no true differences. A standard remedy for this sort (continued)

- A filtering process was employed such that predictors initially identified as being "good" were tested in further combinations. Eventually, we ended up with a set of possible predictors for each model, not all of which could be used in the same model, e.g., multiple measures of the same phenomenon. Final selections were made either on the basis of very small differences in statistical significance (significance is not an either/or situation but rather a continuum) or on the basis of our conceptual understanding (discussed previously).

Given the broad list of possible candidates we started out with, the problem was one of choosing the "best" set of explanatory variables to include in our final models. What complicated the choice is that some of the variables are related and, as a consequence, our assessment of how well an individual variable explains variation in a particular outcome measure is a function of how the different predictors were combined. Even with efficient techniques for systematically searching among the most promising combinations of explanatory variables (without examining all possible combinations), the number of explanatory variables (about 70) put such a strategy beyond our available resources. To the extent possible, predictors were tested individually or in very limited combinations with unrelated variables. The results were sufficiently robust (i.e., in most instances variables were good predictors regardless of the combinations in which they were tested) to convince us that our decisions regarding which variables to include in the final specification were not seriously affected by the way in which the variables were tested for inclusion. Moreover, for the most part the variables selected were similar to the findings reported by previous researchers, which provides some additional support for our choices.

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of difficulty is to apply Bonferroni's inequality, which needs no assumption of independence. If we are simultaneously testing k estimates, we can preserve the overall .05 significance level by testing each of the k estimates at the (individual) .05/k level. Then the probability of getting one or more significant outcomes by chance alone can be no greater than .05. For 50 estimates this implies that we should apply an individual significance level of .05/50 = .001 to each comparison; to be judged reliable, the difference must be significant at, or below, this level. For a complete discussion see Miller, Rupert G., Simultaneous Statistical Inference, 2nd edition, Springer-Verlag, New York, 1981.

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Finally, a concern has arisen regarding the possible extent to which the State indicator variables may "mask" the effect of the socioeconomic variables. When added to a model that already contains the State indicators, these variables can capture only variation that exists within States with regard to these measures. That is, the State indicator variables capture all of the between-State variation. The only way that such effects could be masked, then, is if most of the variation in these measures is accounted for by among-State differences. We tested this possibility for population density, using analysis of variance, and concluded that the within-State variation is substantial after accounting for differences that exist among the States (close to 60 percent of the total variation is within States).

This issue arises largely as a result of the nature of the models we have chosen to estimate. If we had either estimated separate models for each State or used interaction terms to control for the joint relationships between the characteristics and the State indicator variables, this problem would have been avoided. Both alternatives, however, were unacceptable. Separate models, as discussed earlier, would have not permitted us to adjust States on a comparable basis, i.e., our approach assumes that the process of error is the same everywhere and what produces differences is related to variation among States on various characteristics. The use of interaction terms would have made the models nearly impossible to estimate (and interpret) because of the geometric growth in the number of variables in the models.

Calculating Adjusted State Error Rates

The statistical models described in the previous section yield five numbers for each State:

- An adjusted mean food stamp allotment per case-month.
- An adjusted incidence of overpayment error per case-month of benefits.
- An adjusted mean overpayment error amount per overpaid case-month.
- An adjusted incidence of ineligibility error per case-month of benefits.
- An adjusted mean ineligibility error amount per ineligible case-month.

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The problem now is one of deciding how to use these results to calculate an overall adjusted error rate for each State and how to test whether the adjusted error rate is significantly different (in a statistical sense) from the State's reported error rate.

For a particular State i, we calculate the adjusted payment error rate (PER_A) as follows:

$$PER_A = \frac{I_O \exp\{\bar{e}_O + \tfrac{1}{2} s_O^2\} + I_I \exp\{\bar{e}_I + \tfrac{1}{2} s_I^2\}}{\bar{A}}$$

where: I_O = adjusted incidence of overpayment error;

I_I = adjusted incidence of ineligibility error;

$\bar{e}_I$ = adjusted mean log of ineligibility error amount;

s_O^2 = residual mean square from overpayment amount model (d.f. = n_O);

s_I^2 = residual mean square from ineligibility amount model (d.f. = n_I); and

$\bar{A}$ = adjusted mean allotment amount.

The expression $\exp\{\bar{e}_O + \tfrac{1}{2} s_O^2\}$ converts the estimated State mean back to the dollar scale from the logarithmic scale. The variance of the adjusted error rate is equal to:

$$Var(PER_A) = \frac{1}{\bar{A}^4} [\bar{A}^2 \, Var(I_O \exp\{\bar{e}_O + \tfrac{1}{2} s_O^2\}) + \bar{A}^2 \, Var(I_I$$

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and similarly for ineligibility.

To test the significance of the difference between the adjusted error rate (PER_A) and the reported error rate (PER_R), we can write the variance of the difference as follows:

$$Var(PER_A - PER_R) = Var(PER_A) + Var(PER_R) - 2\ cov(PER_A, PER_R)$$

In the present situation we cannot assume that PER_A and PER_R have zero covariance. Instead, it is more plausible (but not certain) that the variability in the adjustment, ($PER_A - PER_R$), is unrelated to the variability in a State's reported error rate. Thus, we write:

$$PER_A = (PER_A - PER_R) + PER_R$$

$$cov(PER_A, PER_R) = cov\{(PER_A - PER_R), PER_R\} + Var(PER_R) \approx Var(PER_R)$$

so that

$$Var(PER_A - PER_R) \approx Var(PER_A) - Var(PER_R)$$

and thus,

$$S.E.(PER_A - PER_R) \approx (Var(PER_A) - Var(PER_R))^{1/2}$$

Therefore, the ratio of the difference to its (approximate) standard error (i.e. the t-statistic) is equal to:

$$t = \frac{(PER_A - PER_R)}{S.E.(PER_A - PER_R)}$$

Chapter IV reports the results of these calculations for each State

Alternative Models

For the purposes of this analsyis, we have decomposed the payment error rate into five components, obtained adjusted means by modeling each component separately, and then assembled these individual estimates to compute an adjusted payment error rate for each State. One important reason for the use of this disaggregated approach was the fact that the data on error amounts are "left-censored." That is, when a

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case is overpaid or ineligible, we know the amount of the error; but when a case is classified as correct, we know only that its error amount does not exceed \$5.00. (Recall that for the purposes of the payment error rate, a case that received an underpayment is regarded as having a zero overpayment, not a negative overpayment; and if its overpayment does not exceed \$5.00, it is classified as correct.) We do, however, have information on the characteristics of each case, except for occasional missing data. A second reason for the choice of our model was the empirical observation that separate models for overpaid cases and ineligible cases provided a more satisfactory fit than a single model that combined the two types of errors.

For data that involve such a left-censored dependent variable and one or more explanatory variables, it is often appropriate to consider the so-called tobit model.35/ This approach introduces a latent dependent variable, y^*, whose value is observed (as y) only if y^* exceeds a known threshold (which may vary from observation to observation). Thus, instead of the multiple regression model,

$$y_i^* = x_i\beta + u_i,$$

in which x_i is a row rector of values of the explanatory variables and β is a column vector of regression coefficients, one has the censored regression model

$$\begin{aligned} y_i^* &= x_i\beta + u_i \\ y_i &= y_i^* \text{ if } y_i^* > c \\ &= \text{undefined otherwise.} \end{aligned}$$

In practice, one sometimes assigns $y_i = c$ for censored observations, but these are not treated as ordinary y-values. Instead an indicator variable identifies the observations as censored, and y_i merely provides a convenient place to store the censoring threshold for observation i.

35/Tobin, James, "Estimation of Relationships for Limited Dependent Variables", Econometrica, 26, 1958, 24-36. For a further discussion of the tobit model, see Maddala, G.S., Limited-dependent and Qualitative Variables in Econometrics, Cambridge University Press, Cambridge, England, 1983, pp. 151-158.

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> In the tobit procedure, the calculation of the estimated regression coefficients is done by the method of maximum likelihood. Briefly, this standard method specifies a probability model (often the normal distribution) for the behavior of the fluctuation term u_i, applies that model to the data to get a likelihood function, and then maximizes that likelihood as a function of the regression parameters. In short, it determines the value of β for which the observed data are the most likely outcome.

The applicability of the tobit model depends critically on the specification of the distribution of the u_i. Specifically, u_i is assumed to have a continuous distribution so that, in particular, there is no discrete probability that y_i^* (the underlying continuous error) is exactly zero. In the context of this study, this would imply that the process that generates a payment error simultaneously determines both the probability that the error occurs and the expected amount of the error, if it does occur.

There are, however, good reasons to expect that the food stamp payment error data will not meet this requirement of the tobit model. For example, the size of an ineligibility error is the amount of the allotment made to the ineligible recipient. To be eligible, a recipient must meet certain requirements, such as limits on assets and work registration, which do not otherwise affect the average allotment. Thus errors in eligibility due to these requirements are not directly tied to the average size of the error. More generally, many errors arise from changes in recipient circumstances over time. It seems quite likely that the probability of some of these changes may be unrelated to the size of the error involved. For example, an unrecognized change in household size generates a fixed payment error, so that the amount of the error cannot be related to the probability that the error may occur. Finally, the size of the payment errors is bounded above by the difference between the maximum allotment and the correct payment, so that the tobit formulation will not apply (unless error amounts almost never reach this bound).

As a consequence, when we attempted to fit a tobit model to a subset of the FY84 QC sample, the result was unsatisfactory. The parameter estimates suggested that a single latent variable was not an adequate description of both the censoring mechanism and the amount of the overpayment error. Fitting separate tobit models to the overpaid cases and the ineligible cases yielded similar results. Thus, the data seem to require

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separate models for incidence and amount and a separate treatment of overpayments and payments to ineligible cases as we have done in this study.

The tobit model can be extended to allow for a closer connection between the amount of error and the incidence of error. This is done by parameterizing the connection between the observed error, y_i, and the process that determines incidence, y_i^*. That is, we specify

$$y_i^* = x_i\beta + u_i$$

$$y_i = \begin{cases} z_i\gamma + \theta E(u_i \mid y_i^* > c) + e, & \text{if } y_i^* > c \\ \text{undefined if } y_i^* \leq c \end{cases}$$

The differences from the tobit model are that y_i may have different regressors (z_i) from y_i^* and that the expected value of u_i is allowed to affect y_i by the factor θ instead of on a dollar-for-dollar basis.36/

Interestingly, in the context of the linear probability models used in this report, this model is exactly the one tested. To see this, assume that u_i has a uniform distribution over some range, (a, b). Then,

$$\text{Prob(error)} = \text{Prob}(x_i\beta + u_i > c)$$

$$= \frac{b - (c - x_i\beta)}{b-a}$$

assuming, of course, that $(c - x_i\beta) \leq b$. In this case,

$$E(u_i \mid y_i^* > c) = \frac{b + (c - x_i\beta)}{2}$$

36/See, for example, James J. Heckman, "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models," Annals of Economic and Social Measurement, 5, 1976, 475-492.

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Thus, for positive errors,

$$y_i = z_i\gamma + \frac{b + c}{2} - \frac{x_i\beta}{2} + e$$

Therefore, we need only include all the determinants of incidence, x_i, as candidate variables in the error amount regressions. This was, in fact, the procedure used to specify our models though some variables were subsequently dropped when they proved statistically insignificant.

The model can also be applied with nonlinear probability models for error incidence. The computations become more difficult, however, and we were not able to pursue this alternative within the scope of this project. If policymakers decide to proceed with an adjustment model, it would be desirable to examine the use of such techniques in detail.

In summary, we can conclude that our approach based on the use of five separate components of the error process, involves little bias in estimating the adjusted mean amounts of overpayments to eligible cases and payments to ineligible cases. Empirical evidence suggests that lognormal distributions provide an adequate approximation to the behavior of error amounts among overpaid and ineligible cases. In this situation the expression exp $\{\bar{e}_O + \frac{1}{2} S_O^2\}$ (for example) arises as the leading term of the minimum-variance unbiased estimate of the mean of the lognormal distribution. Further terms depend on $\frac{1}{2} S_O^2$ and the sample size, but $\frac{1}{2} S_O^2$ is small enough (roughly 0.4) and the sample size is large enough that we may neglect those terms. The major remaining source of possible bias is the fact that error amounts smaller than \$6.00 are regarded as zero, but this constraint is part of the definition of the payment error rate--for reported error rates and adjusted error rates alike.

IV ANALYTIC RESULTS

This chapter presents the results of our attempts to develop statistical models of State payment errors[37/]. The chapter is divided into eight sections. The first five focus, in turn, on each of the models that form the basis for our calculation of adjusted State error rates. The sixth summarizes the separate results. In the seventh section, we put the individual pieces together and compare our results to the States' reported error rates. In the last section, we examine the importance of the adjustments. The following chapter takes a closer look at the sensitivity of the analytic results to different model specifications and assesses the stability of the findings by applying the model to data for FY 85.

Before presenting the results of our modelling effort, however, it is important to reiterate a point from the previous chapter. This is an exploratory research effort and one for which we do not have a strong theory. We have depended instead on prior research efforts and the opinions of program experts (including the two recent legislative proposals previously discussed in Chapter I) to identify possible factors on which to base an adjustment procedure.

The reader is, therefore, cautioned regarding the interpretation of the specific variables that are included in the models to be discussed in the remainder of this chapter. Our decision to include certain variables and exclude others was based upon both statistical criteria (the best predictive ability) and our understanding of the context in which the data arise, i.e., how particular features of the Food Stamp Program can affect the likelihood of error. Alternative models could be estimated for each of the five outcome measures that comprise a State's payment error rate. Moreover, because the estimated effect of a particular variable depends upon what else is in the model, one could conclude something different about the "causes" of error under these different specifications.

As a consequence, the models should be viewed in their entirety without placing too much emphasis on the effect of a particular

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37/The error rates discussed in this report refer to the State's reported error rate. We have not included a consideration of the effect of the Federal re-review process on final reported error rates. Therefore, the figures presented are not fully comparable to the official program payment error rates provided in Chapter I.

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characteristic variable. As will be shown in the following chapter, relatively small changes in the specification of these models can produce different adjustments to the State means.

Food Stamp Allotment

As discussed in Chapter III, the variables included in the model for the size of a household's food stamp benefits are those factors used to calculate allotments:

- Total reported earned income
- Deductions for medical costs
- Deductions for dependent care costs
- Total AFDC grant
- Total unearned income less AFDC
- Number of case members
- Reported shelter costs (rather than the computed deduction)

The model (shown in Exhibit 4.1) has, not surprisingly, excellent explanatory power -- accounting for about 87 percent of the variation in benefit amounts (i.e., the value of R^2 is 0.8659), and the coefficients of all seven factors are significant (as indicated by the value of the t-statistic in column 4).38/

In a separate regression, the model with State indicator variables alone accounted for about 4.6 percent of the variation in food stamp benefit amounts. This means that caseload characteristics account for about 82 percent of the variation in food stamp allotments among States.

38/The models discussed in this Chapter have all been estimated without a constant term. This approach directly yields each State's adjusted mean on the individual dependent variables. This approach, however, also results in regression statistics that are different from a more conventionally accepted form. For example, excluding a constant term redefines R^2 to represent variation about zero, as opposed to the more conventional variation about the mean of the dependent variable. For the sake of clarity, we have recalculated the regression statistics so as to express them in the customary form. Exhibits 4.1 through 4.5 present the adjusted statistics.

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EXHIBIT 4.1

Statistical Model for Food Stamp Allotment

SOURCE	DF	SUM OF SQUARES	MEAN SQUARED	F VALUE
MODEL	56	4.041E+08	7.214E+06	73970.9
ERROR	64286	0.626E+08	975.252	
U TOTAL	64342	4.667E+08		

ROOT MSE	31.229022	R-SQUARED	0.8659
DEP MEAN	119.010		
C.V.	26.24067		

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	t STATISTIC
Total Earned Income	-0.193	0.000670	-287.356
Med. Deductions	0.174	0.007573	22.992
Dep. Care Deductions	0.142	0.008839	16.035
AFDC Grant	-0.178	0.001020	-174.846
All Other Unearned Income	-0.220	0.000749	-293.910
Number of Case Members	48.701	0.091366	533.035
Shelter Costs	0.042	0.000979	42.508
AL	114.976	0.645835	-6.129
AK	205.755	1.815361	47.676
AZ	117.169	0.651373	-2.775
AR	113.637	0.884068	-6.015
CA	96.207	0.734155	-30.620
CO	113.950	0.746598	-6.687
CN	107.698	0.917570	-12.216
DE	115.455	1.581686	-2.237
DC	116.061	1.258959	-2.332
FL	119.931	0.632817	1.427
GA	115.433	0.893193	-3.970
HA	189.532	1.039070	67.395
ID	119.058	1.228864	0.040
IN	119.715	0.750535	0.933
IA	112.889	0.907287	-6.683
KS	117.140	0.957879	-1.936
KY	117.374	0.720029	-2.245
LA	115.608	0.982488	-3.433
ME	116.812	0.973218	-2.242
MD	119.635	0.897478	0.695
MA	117.852	1.036467	-1.111
MI	120.882	0.659646	2.786
MN	103.602	0.886142	-17.225
MS	118.983	0.923608	-0.032
MO	114.191	0.630210	-7.506
MT	111.513	1.140063	-6.540
NB	109.531	0.912281	-10.297
NV	115.616	1.386269	-2.435
NH	118.160	1.336197	-0.633
NJ	118.377	0.667754	-0.927
NM	116.526	0.708830	-3.447
NY	120.451	1.487547	0.964
NC	112.715	0.905355	-6.883
ND	112.054	1.600907	-4.334
OH	119.961	0.640894	1.455
OK	111.347	0.831271	-9.115
OR	143.282	0.940099	25.597
PA	116.235	0.903298	-3.038
RI	121.197	0.916096	2.369
SC	120.500	0.788542	1.867
SD	119.199	1.344012	0.140
TN	113.467	0.896805	-6.120
TX	114.056	0.924444	-5.307
UT	112.819	1.484065	-4.156
VT	120.544	1.206482	1.261
VA	110.093	1.302997	-6.815
WA	112.246	0.638311	-10.398
WV	122.243	0.916034	3.494
WI	98.494	0.599793	-33.512
WY	116.270	1.719886	-1.589

For each variable (listed in column 1), Exhibit 4.1 also provides the size of the estimated coefficient (column 2) and its associated standard error or measure of variability (column 3). The coefficient associated with each of the State variables, as described in Chapter 3, represents the average food stamp benefit adjusted for the effect of the caseload characteristics that have been included in this model. For example, the adjusted mean for Alabama (the first State listed) is $114.98 (later in this chapter we will compare these adjusted values to the reported means).

An examination of the coefficients on the individual caseload factors is also instructive. First, the directions of their effects are as one would expect: an increase in earned income, AFDC and other unearned income is expected to decrease the size of the food stamp benefit (other things being equal); and an increase in deductions, shelter costs or the size of the household is expected to increase the size of the allotment. For example, allowing for simultaneous change in other factors, increasing the household size by one member will increase the size of the benefit by about $49 on average. (Later in this chapter, we show how these individual factors lead to the adjusted State mean.)

Incidence Of Overpayment Error

Exhibit 4.2 presents the regression model for the incidence of overpayment error (the columns are the same as described above). The dependent variable in this model is equal to "1" if the case has an overpayment error and equal to "0" otherwise. In this type of equation, known as a linear probability model, the coefficient on a particular characteristic variable can be interpreted as the added probability of overpayment error due to a unit change in the particular variable (e.g., the addition of another person to the case). The parameter estimates for the State indicator variables represent the adjusted probability of error (i.e., the expected proportion of cases with overpayment error if the State had a caseload with characteristics like the national average).

In this instance, six characteristics were found to be significantly related to the incidence of overpayment error:

EXHIBIT 4.2

Statistical Model for Incidence of Overpayment Error

SOURCE	DF	SUM OF SQUARES	MEAN SQUARED	F VALUE
MODEL	55	224.59	4.083453	39.874
ERROR	64287	6583.59	0.102409	
U TOTAL	64342	6808.18		

ROOT MSE	0.320015	R-SQUARED	0.0330
DEP MEAN	0.120277		
C.V.	266.064		

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	t STATISTIC
True Presence of Earnings	0.048032	0.0032303	14.869
Number of Deductions	0.049375	0.0020949	23.570
Number of Persons Receiving Institutional Unearned Income	0.041885	0.0024994	16.758
Presence of AFDC	0.016873	0.0027311	6.178
Number Persons Aged 18-59	0.035003	0.0016458	21.269
Population Density	0.000005	0.0000008	6.289
AL	0.134628	0.0066025	2.191
AK	0.125951	0.0186110	0.310
AZ	0.167038	0.0066808	6.953
AR	0.119237	0.0090587	-0.140
CA	0.098876	0.0072512	-2.872
CO	0.127640	0.0764687	1.002
CN	0.114663	0.0093431	-0.661
DE	0.105240	0.0162110	-0.945
DC	0.096643	0.0146960	-1.577
FL	0.128365	0.0064927	4.106
GA	0.157706	0.0091520	4.406
HA	0.072809	0.0106330	-4.388
ID	0.104883	0.0126130	-1.206
IN	0.142888	0.0076578	2.912
IA	0.133681	0.0093291	1.462
KS	0.096562	0.0098412	-2.355
KY	0.129195	0.0073739	1.162
LA	0.123301	0.0100610	0.369
ME	0.090678	0.0099706	-2.904
MD	0.089746	0.0099329	-3.260
MA	0.135090	0.0105590	1.329
MI	0.111690	0.0067465	-1.214
MN	0.126203	0.0090523	0.622
MS	0.142840	0.0094782	2.527
MO	0.124636	0.0064678	1.015
MT	0.139691	0.0117170	0.963
NB	0.106986	0.0093654	-1.414
NV	0.048886	0.0142280	-5.070
NH	0.111789	0.0137160	-0.601
NJ	0.104378	0.0072690	-2.062
NM	0.142086	0.0072723	2.971
NY	0.111186	0.0152010	-0.608
NC	0.090517	0.0092752	-3.260
ND	0.063647	0.0164270	-3.421
OH	0.115256	0.0065572	-0.785
OK	0.100701	0.0085466	-2.243
OR	0.111333	0.0096755	-0.958
PA	0.123954	0.0095553	0.384
RI	0.123469	0.0093663	0.287
SC	0.159757	0.0080769	4.845
SD	0.088324	0.0137990	-2.329
TN	0.109607	0.0091629	-1.106
TX	0.118772	0.0094300	-0.136
UT	0.098380	0.0152180	-1.460
VT	0.130465	0.0123870	0.780
VA	0.099781	0.0133540	-1.517
WA	0.126757	0.0065563	1.015
WV	0.123215	0.0093941	0.287
WI	0.094050	0.0059326	-4.355
WY	0.107151	0.0176460	-0.748

- "True" presence of earnings[39]
- Number of deductions
- Number of persons with other "institutional" unearned income (includes any of the following--RSDI, Veterans Benefits, Unemployment Compensation, Workmen's Compensation and Disability)
- Presence of AFDC
- Number of persons aged 18-59
- Population density

In each instance, an increase in the individual factor tends to increase the probability of an overpayment error. For example, having earnings is related to a higher probability of overpayment error.

Overall, the model accounts for 3.3 percent of the variation in the probability of an overpayment error. A model consisting of only the State indicator variables explains about 0.5 percent of the variation. Therefore, caseload and socioeconomic characteristics alone explain about 2.8 percent of the variation.

The variables that are strong predictors in this model are quite reasonable, i.e., the presence of earned income, the number of adults (potential wage earners), the number of occurrences of various types of unearned income and deductions (greater opportunities for error in more complex cases) and the "urbanicity" of the area in which the household resides. Of equal interest, however, is what is <u>not</u> here -- factors that were tested in alternative specifications of the statistical model as possible predictors of overpayment error but which were found to be statistically insignificant:

- <u>Assets</u> -- As discussed in Chapter III, assets are only used to determine eligibility. Underreporting assets will lead to an error only if the total exceeds the asset limit, rendering the household ineligible.

- <u>The dollar value of deductions and the amount of various types of income</u> -- the empirical evidence suggests that it is the number of different sources of income or the number

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39/True values incorporate the findings of the QC verification process.

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of deductions that better predict the probability of error rather than their magnitude. For example, having a larger number of households with multiple sources of income is more likely to lead to higher error rates than having more single-income-source households, even if the total earnings are the same.

- Household demographic characteristics -- Gender and ethnicity do not appear to influence the probability of overpayment. Similarly, other than the number of adults in the household, neither the age composition of the case nor the presence of an elderly or disabled person increases the likelihood of an overpayment error.

- Program features -- Factors such as work registration requirements and the receipt of expedited services do not appear to be influential. Similarly, eligibility for AFDC-U benefits does not seem to contribute to the likelihood of an overpayment error.

- Other socioeconomic variables -- Measures of the social environment in which the household resides other than population density either were found not to influence the potential for overpayment error or, in the case of crime rate, were found not to be as good a predictor as population density (both could not be included in the same model because of collinearity problems). Because many of the variables capture the same underlying phenomena (i.e., they distinguish inner-city, high-poverty places), their interrelationship is such that they do not work well together in the same model specification. We have, therefore, left the most significant predictor in the model and excluded the rest.

It is not that these variables are unrelated to error, but rather that they have no effect over and above the effect due to other differences among the States. As we will see below, these factors are, with few exceptions, also excluded from all of the other models.

Amount Of Overpayment Error

The model for the amount of an overpayment error is shown in Exhibit 4.3. Overall, this model explains about 6 percent of the variation in the size of overpayment errors, with caseload characteristics alone explaining about 4.7 percent.

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EXHIBIT 4.3

Statistical Model for the Amount of an Overpayment Error

SOURCE	DF	SUM OF SQUARES	MEAN SQUARED	F VALUE
MODEL	53	383.932	7.244	9.559
ERROR	7991	6055.630	0.757806	
U TOTAL	8044	6439.562		

ROOT MSE	0.870521	R-SQUARED	0.0596
DEP MEAN	3.365382		
C.V.	25.86692		

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	t STATISTIC
Total Earned Income	-0.000547	0.000049	-11.153
AFDC Grant	-0.000709	0.000080	-8.853
All Other Unearned Income	-0.000591	0.000055	-10.720
Number of Case Members	0.119288	0.006562	18.178
AL	3.246336	0.048367	-2.418
AK	3.842504	0.145563	3.266
AZ	3.361520	0.044902	-0.073
AR	3.199218	0.071055	-2.318
CA	3.343337	0.066311	-0.334
CO	3.471304	0.057941	1.799
CN	3.355901	0.080868	-0.115
DE	3.378788	0.134444	0.101
DC	3.478858	0.093958	1.202
FL	3.351666	0.050309	-0.261
GA	3.278375	0.062716	-1.377
HA	3.293915	0.112692	-0.629
ID	3.354113	0.101456	-0.111
IN	3.399094	0.054877	0.602
IA	3.268411	0.069552	-1.371
KS	3.211079	0.085800	-1.787
KY	3.357690	0.053472	-0.540
LA	3.399018	0.070222	0.474
ME	3.156380	0.087993	-2.365
MD	3.355677	0.076955	-0.120
MA	3.464473	0.071108	1.374
MI	3.254754	0.056339	-1.932
MN	3.211164	0.070966	-2.154
MS	3.176038	0.064340	-2.912
MO	3.175824	0.048255	-3.851
MT	3.299473	0.085483	-0.771
NB	3.351994	0.077036	-0.172
NV	3.566367	0.224903	0.891
NH	3.531927	0.119611	1.388
NJ	3.415273	0.055049	0.888
NM	3.343568	0.052497	-0.400
NY	3.400906	0.068167	0.517
NC	3.371617	0.082847	0.079
ND	3.361825	0.174131	-0.019
OH	3.317000	0.052262	-0.909
OK	3.430690	0.076765	0.847
OR	3.451096	0.080013	1.062
PA	3.212864	0.067808	-2.224
RI	3.402568	0.075922	0.491
SC	3.285755	0.053429	-1.462
SD	3.080012	0.120898	-2.352
TN	3.260654	0.074412	-1.404
TX	3.265658	0.074508	-1.322
UT	3.582190	0.105625	2.042
VT	3.389479	0.094552	0.248
VA	3.311562	0.083486	-0.635
WA	3.409399	0.051705	0.829
WV	3.224345	0.071585	-1.956
WI	3.399661	0.051333	0.663
WY	3.429393	0.145275	0.436

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Incidence Of Ineligibility Error

The model for the incidence of ineligibility error is presented in Exhibit 4.4. Nine characteristics appear to be strong predictors in this instance:

- Total household wage income
- Presence of AFDC
- Number of persons receiving SSI benefits
- Number of persons with other "institutional" unearned income
- Number of persons aged 18-59
- "True" presence of liquid resources, real property and vehicles (three separate variables)
- Population density

Because ineligibility errors are relatively rare events (overall only about 4 percent of the cases have such errors), the explanatory power of this model is lower than in the other models presented thus far. In total, the model accounts for only about 2.3 percent of the variation (caseload and socioeconomic characteristics together explain about 2 percent of the variation). However, the coefficients on the nine factors are highly significant, as are most of the State indicator variables (those that are not have very few ineligible cases). Consequently, even though the overall explanatory power of the model is low, the included caseload and socioeconomic characteristics have an important effect on the incidence of ineligibility error.

Seven factors are positively related to the probability of this type of error -- population density, the magnitude of the household's wage income, the number of occurrences of different types of institutional unearned income, the number of adult household members, and the presence of the three types of assets. Increasing the representation of any of these factors in a State's caseload would be expected to increase the likelihood of ineligibility error. Conversely, the receipt of AFDC[40] or SSI benefits tends to decrease the probability of ineligibility error.

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EXHIBIT 4.4

Statistical Model for the Incidence of Ineligibility Error

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	58	56.448	0.973240	25.813
ERROR	64284	2423.780	0.037704	
U TOTAL	64342	2480.228		

ROOT MSE	0.194176	R-SQUARED	0.0227
DEP MEAN	0.040160		
C.V.	483.5083		

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	t STATISTIC
Total Wage Income	0.000046	0.0000036	12.711
Presence of AFDC	-0.017428	0.0017107	-10.188
Number persons with SSI	-0.017586	0.0019706	-8.924
Number Persons with Institutional Unearned Unearned Income	0.020906	0.0015521	13.469
Number Persons Aged 18-59	0.008248	0.0010618	7.768
True Presence of Liq. Resources	0.014446	0.0017555	8.229
True Presence of Real Property	0.185407	0.010019	18.506
True Presence of Vehicles	0.032514	0.0043653	7.448
Population Density	0.000003	0.0000005	5.975
AL	0.036972	0.0040138	-0.775
AK	0.045628	0.0112900	0.515
AZ	0.044928	0.0040537	1.160
AR	0.046144	0.0055008	1.051
CA	0.039093	0.0044078	-0.259
CO	0.047801	0.0046423	1.681
CN	0.042587	0.0056717	0.493
DE	0.034428	0.0098392	-0.626
DC	0.018584	0.0089192	2.368
FL	0.035694	0.0039462	-1.046
GA	0.047936	0.0055567	1.210
HA	0.021017	0.0064599	-2.927
ID	0.033364	0.0076551	-0.937
IN	0.031572	0.0046479	-1.713
IA	0.043010	0.0056750	0.493
KS	0.045010	0.0059737	0.800
KY	0.044367	0.0044771	0.841
LA	0.04 040	0.0061120	1.275
ME	0.034196	0.0060553	1.001
MD	0.027713	0.0060276	-2.010
MA	0.046884	0.0064267	1.061
MI	0.037579	0.0040978	-0.517
MN	0.044828	0.0055097	0.871
MS	0.044889	0.0057639	0.827
MO	0.019551	0.0039435	-5.072
MT	0.039879	0.0071132	-0.022
NB	0.043759	0.0057049	0.667
NV	0.006196	0.0086334	-4.002
NH	0.042872	0.0083287	0.340
NJ	0.044648	0.0044099	1.083
NM	0.053631	0.0044111	3.098
NY	0.052851	0.0092231	1.390
NC	0.026088	0.0056316	-2.505
ND	0.020206	0.0100760	1.990
OH	0.047047	0.0039834	1.679
OK	0.038688	0.0051943	-0.220
OR	0.029051	0.0058768	-1.875
PA	0.034993	0.0058686	-0.867
RI	0.037669	0.0056843	-0.382
SC	0.051061	0.0049116	2.185
SD	0.022078	0.0083789	-2.152
TN	0.023513	0.0055616	-3.036
TX	0.046242	0.0057250	1.015
UT	0.052903	0.0092352	1.390
VT	0.048957	0.0075242	1.172
VA	0.032228	0.0081044	-1.002
WA	0.048123	0.0039830	1.925
WV	0.033515	0.0057036	-1.244
WI	0.045436	0.0036345	1.315
WY	0.057981	0.0107110	1.663

The primary relationship appears to be, then, that: more urbanized places and caseloads with a higher proportion of households with earnings (or at least the potential for earnings as measured by the number of adults) and assets have a greater likelihood of ineligibility error; and caseloads with a higher proportion of households with public assistance benefits have a lower likelihood of such an error.

Amount Of Ineligibility Error

Given that an ineligibility error occurs, Exhibit 4.5 presents the model which examines the factors that influence the magnitude of such an error (this model is based on only those cases found to be ineligible). Four variables were found to be good predictors in this instance:

- Total household earned income
- Total AFDC benefits
- Total unearned income other than AFDC
- Number of persons in the case

With the exception of deductions, the specification of this model is quite similar to that for the amount of the food stamp allotment. This is not unexpected because, when an ineligibility error occurs, the size of the error is simply the full amount of the food stamp allotment.

Overall, the model accounts for almost 27 percent of the variation in error amount, and the coefficients on the four factors are all highly significant. The caseload characteristics themselves explain almost 21 percent of the observed variation in error amounts. The comparatively high explanatory power of this model is due to the relationship noted above between the allotment and the size of this type of error.

Because this model (and that for the amount of an overpayment error) is estimated using the lognormal distribution, the contributions of the variables to the amount of error are multiplicative. As a result the interpretation of the individual effects of the caseload characteristics is not quite as straightforward as in the incidence models. However, the direction of the effects is what we would expect given the relationship to the household's food stamp allotment; i.e., increasing earned income, AFDC benefits or other unearned income tends to decrease the size of the overpayment, whereas increasing the size of the household tends to increase the size of the overpayment. Factors which produce higher average food stamp allotments will also tend to produce larger ineligibility errors.

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EXHIBIT 4.5
Statistical Model for the Amount of an Ineligibility Error

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	53	662.564	12.5012	18.1313
ERROR	2628	1811.952	0.689480	
U TOTAL	2681	2474.516		

ROOT MSE	0.830349	R-SQUARED	0.2678
DEP MEAN	4.260132		
C.V.	19.49116		

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	t STATISTIC
Total Earned Income	-0.001088	0.000072	14.966
AFDC Grant	-0.000839	0.000137	-6.091
ALL Other Unearned Income	-0.001616	0.000089	-18.084
Number of Case Members	0.255845	0.011928	21.449
AL	4.283911	0.085037	0.136
AK	5.455922	0.224208	3.832
AZ	4.517637	0.080986	2.904
AR	4.295355	0.103493	0.027
CA	4.488455	0.105991	2.164
CO	4.457839	0.090543	2.086
CN	4.260195	0.133667	-0.116
DE	4.515087	0.240595	1.028
DC	4.618890	0.181320	1.843
FL	4.468952	0.094341	2.059
GA	4.459886	0.113609	1.657
HA	5.124023	0.181255	4.582
ID	4.399556	0.169823	0.805
IN	4.445681	0.106499	1.599
IA	4.242074	0.115505	-0.172
KS	4.009580	0.120467	-0.452
KY	4.454659	0.088685	2.021
LA	4.538830	0.111229	1.831
ME	4.404749	0.135179	1.031
MD	4.564220	0.129961	2.289
MA	4.667568	0.123496	3.245
MI	4.457990	0.099138	2.008
MN	4.227815	0.110193	-0.260
MS	4.254615	0.108332	-0.137
MO	4.117128	0.101577	-1.426
MT	4.439580	0.147152	1.150
NB	4.108506	0.108615	-1.436
NV	4.173170	0.587354	-0.130
NH	4.311829	0.25.407	0.400
NJ	4.255604	0.085270	-0.001
NM	4.452710	0.079345	1.536
NY	4.373257	0.107466	1.457
NC	3.791127	0.135559	-3.513
ND	4.070560	0.222172	-0.908
OH	4.284868	0.080903	0.288
OK	3.779681	0.114592	-4.152
OR	4.519986	0.181541	1.426
PA	4.383577	0.098838	1.242
RI	4.278297	0.131876	-0.364
SC	4.271817	0.095854	0.039
SD	3.780987	0.208389	-2.347
TN	4.255658	0.144936	-0.028
TX	4.023954	0.111313	-2.234
UT	4.233451	0.154287	-0.508
VT	4.082386	0.138557	-1.280
VA	3.972255	0.133075	-2.158
WA	4.287929	0.080774	1.191
WV	4.334825	0.137251	0.460
WI	4.178022	0.074814	-0.924
WY	4.121525	0.185823	-0.781

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Summary Of Statistical Models

Exhibit 4.6 provides a summary of the effect of the case and socioeconomic factors on the five separate components of a State's payment error rate. For each component, this table presents both the State-reported value (derived from the IQCS data) and the adjusted value derived from the statistical models.

For example, consider Alabama. If Alabama's caseload had the characteristics of the national average, its:

- Average food stamp allotment would decrease from $119 to $115.
- Average incidence of overpayment error would decrease from 14 percent to 13.5 percent.
- Average incidence of ineligibility error would decrease from 4.1 percent to 3.7 percent.
- Average overpayment error amount would decrease from $42.0 to $37.5.
- Average ineligibility error amount would increase from $88.3 to $101.4.

In general, then, Alabama's caseload is such that if it had clients more like the national average, it would be expected to have a lower error rate than was reported for FY84. A similar examination of the effects can be performed for the other States.

A look at the caseload characteristics that appear in the separate models reveals an interesting pattern (see Exhibit 4.7). For the most part, six types of factors appear to affect the process of food stamp error:

- Household Size -- Appears in all five models and is always positively related (i.e., an increase in household size increases the respective outcomes measures).
- Earned Income -- Appears in all five models -- positively related in the incidence equations, and negatively related in the allotment and error amount models.

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EXHIBIT 4.6

Components of Adjusted State Payment Error Rates

State	Allotment		Incidence of Overpayment Error		Incidence of Ineligibility Error		Amount of Overpayment Error		Amount of Ineligibility Error	
	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted
Alabama	$119	$115	14.0%	13.5%	4.1%	3.7%	$42.0	$37.5	$88.3	$101.4
Alaska	203	206	11.8	12.6	4.6	4.6	76.4	68.1	221.4	292.1
Arizona	144	117	16.6	16.7	4.6	4.5	51.1	42.1	113.8	129.7
Arkansas	112	114	12.1	11.9	5.2	4.6	39.5	35.8	114.6	99.9
California	96	96	9.3	9.9	3.1	3.9	36.4	41.3	100.7	126.5
Colorado	126	114	12.6	12.8	4.7	4.8	47.2	47.0	116.0	121.9
Connecticut	88	108	9.9	11.4	3.3	4.3	39.3	41.9	68.8	98.4
Delaware	116	115	10.5	10.5	3.1	3.4	44.5	42.9	94.5	128.5
District of Columbia	111	116	12.5	9.7	3.2	1.9	43.4	47.4	116.2	141.4
Florida	122	120	12.4	12.8	3.2	3.6	44.4	41.7	120.7	122.1
Georgia	124	115	15.8	15.8	4.4	4.7	44.7	38.7	113.3	121.3
Hawaii	173	190	6.6	7.3	2.3	2.1	39.5	49.4	195.5	236.0
Idaho	128	119	11.4	10.5	3.7	3.3	45.5	41.8	108.2	115.0
Illinois[a]	--	--	--	--	--	--	--	--	--	--
Indiana	138	120	14.6	14.3	3.5	3.2	50.2	43.7	128.5	119.1
Iowa	108	113	13.2	13.4	4.4	4.3	39.7	38.4	83.3	98.2
Kansas	110	117	9.7	9.7	4.5	4.5	35.9	36.2	87.1	94.8
Kentucky	134	117	14.2	12.9	4.7	4.4	46.6	41.1	113.8	120.3
Louisiana	133	115	12.7	12.4	4.6	4.8	53.1	43.7	145.4	125.5
Maine	105	117	9.1	9.1	3.5	3.4	34.2	34.3	99.6	115.3
Maryland	119	120	10.6	9.0	3.4	2.8	41.0	41.9	107.0	135.4

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EXHIBIT 4.6 (continued)

Components of Adjusted State Payment Error Rates

State	Allotment		Incidence of Overpayment Error		Incidence of Ineligibility Error		Amount of Overpayment Error		Amount of Ineligibility Error	
	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted
Massachusetts	92	118	13.2	13.5	3.9	4.7	44.6	46.7	116.1	150.3
Michigan	109	121	10.6	11.2	3.1	3.8	34.9	37.8	98.3	122.8
Minnesota	90	104	12.1	12.6	4.6	4.5	34.7	36.2	78.8	97.3
Mississippi	130	119	15.6	14.4	5.0	4.5	39.6	35.0	89.4	98.7
Missouri	121	114	13.5	12.7	2.7	2.0	40.7	35.0	74.9	86.5
Montana	115	112	13.8	13.2	4.2	4.0	40.9	39.6	94.3	118.9
Nebraska	104	110	10.8	10.7	5.0	4.4	45.9	41.7	81.5	85.5
Nevada	108	116	2.9	4.9	0.4	0.6	74.5	51.7	84.5	92.8
New Hampshire	97	118	9.7	11.2	4.3	4.3	45.4	50.0	83.6	107.4
New Jersey	121	118	11.4	10.5	4.3	4.5	42.3	44.4	92.9	100.2
New Mexico	133	117	14.2	14.2	5.7	5.4	45.4	41.4	126.7	114.1
New York	99	120	12.2	11.1	4.2	5.3	41.4	43.8	108.6	119.2
North Carolina	112	113	9.1	9.0	3.2	2.6	41.0	42.6	70.4	61.9
North Dakota	114	112	6.6	6.4	3.7	2.0	46.2	42.1	112.6	81.9
Ohio	125	120	11.7	11.5	4.4	4.7	40.7	40.3	94.1	102.6
Oklahoma	103	111	9.0	10.1	3.7	3.9	46.5	45.1	67.2	61.9
Oregon	122	143	10.7	11.1	1.9	2.9	44.9	46.1	141.8	129.9
Pennsylvania	109	116	13.8	12.4	5.9	3.5	36.9	36.3	101.1	113.5
Rhode Island	98	121	11.1	12.3	3.5	3.8	39.2	43.9	83.8	94.9
South Carolina	152	120	16.9	16.0	4.7	5.1	42.6	39.1	102.7	100.6
South Dakota	130	119	9.6	8.8	3.0	2.2	29.4	31.8	63.8	61.2
Tennessee	119	113	11.1	11.0	2.7	2.3	39.7	38.1	93.9	99.8
Texas	135	114	11.6	11.9	4.8	4.6	41.5	38.3	98.6	77.9

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EXHIBIT 4.6 (continued)

Components of Adjusted State Payment Error Rates

State	Allotment		Incidence of Overpayment Error		Incidence of Ineligibility Error		Amount of Overpayment Error		Amount of Ineligibility Error	
	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted	Reported	Adjusted
Utah	122	112	9.9	9.8	4.9	5.3	55.0	52.5	96.5	90.6
Vermont	99	121	12.6	13.0	5.3	4.9	36.7	43.3	79.4	83.8
Virginia	110	110	9.8	10.0	3.5	3.2	42.2	40.1	89.8	75.0
Washington	98	112	11.8	12.7	4.4	4.8	41.8	44.2	93.8	111.3
West Virginia	148	122	12.7	12.3	3.2	3.3	40.3	36.7	123.2	106.8
Wisconsin	95	98	10.4	9.4	4.4	4.5	38.8	43.8	82.6	93.3
Wyoming	128	116	10.9	10.7	6.4	5.8	51.9	45.1	97.3	86.6

[a] Illinois was involved in a demonstration during FY84, therefore, its error rates are not comparable to those of other states.

EXHIBIT 4.7

Direction of Effect of Caseload and Socioeconomic Characteristics on Food Stamp Allotment, Incidence and Amount of Payment Error

Variables	Allotment	Overpayment Error Incidence	Overpayment Error Amount	Ineligibility Error Incidence	Ineligibility Error Amount
Household Size					
Number of Case Members	+		+		+
Number of Persons 18-59		+		+	
Earned Income					
Reported Total Earned Income	-		-		-
"True" Presence of Earnings		+			
Reported Total Wage Income				+	
Unearned Income					
Total AFDC Grant	-		-		-
Total Unearned Income other than AFDC	-		-		-
Receipt of AFDC		+		-	
Number of Persons Receiving Institutional Unearned Income		+		+	
Number of Persons Receiving SSI				-	
Resources					
True Presence of Liquid Resources				+	
True Presence of Real Property				+	
True Presence of Vehicles				+	
Deductions					
Medical Deductions	+				
Dependent Care Deductions	+				
Reported Shelter Costs	+				
Total Number of Deductions		+			
Population Density		+		+	

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- Unearned Income -- Appears in all five models but the relationships are not consistent due, in large part, to the presence of other variables in the different equations. For the allotment and error amount models, the relationships are all negative; for the incidence of overpayment error the relationship is positive, whereas for the incidence of ineligibility error, the signs are mixed because of the interaction among the separate measures of unearned income.

- Resources -- Appears in only the model for the incidence of ineligibility error and is related in a positive direction.

- Deductions -- Appears in only two of the five models; positively related to both food stamp allotment and the incidence of overpayment error.

- Population Density -- Appears in both of the incidence models and is positively related in both instances.

The characteristics that appear to influence error rates are relatively few and, by and large, their effect is in the same direction across the separate models. The caseload and socioeconomic characteristics which appear to increase error are higher proportions of households with earners, deductions, assets, and living in more densely populated areas. The effect of household size, however, is indeterminate -- it tends to increase the size of a payment error should one occur (i.e., the numerator of the payment error rate) but also increases the size of the household's allotment (the denominator of the error rate).

Even though the explanatory power of these variables is, for the most part, relatively small (i.e., over and above that due to other differences among the States), they do produce relatively large adjustments to the State means for the five components of payment error that we have modeled. In some situations, however, they produce offsetting adjustments to different components. In Alabama, for example, the adjusted incidence of ineligibility error represented a decrease, whereas the adjusted amount of ineligibility error represented an increase. To see the overall effect, then, the next section combines the five components into an adjusted payment error rate for each State.

Adjusted State Payment Error Rates

This section presents the results of applying the statistical models to calculate an adjusted error rate for each State. The adjusted rates are then compared to the State reported rates to test whether they are significantly different. Both numbers are estimates and have associated standard errors which can be combined to judge the size of the difference between them. Unless the observed difference (relative to its standard error) is too large to have arisen purely by chance, we cannot argue that the adjustment is statistically meaningful; i.e., it does not produce an error rate that is clearly different from that originally reported by the State.

The Adjustments: Exhibit 4.8 provides, for each State, the reported error rate and its standard error (which measures the variability of the estimate), the adjusted error rate and its standard error, the difference between the two rates and the associated t-statistic. The magnitude of the adjustments ranges from a low of 0.02 in Hawaii and Minnesota (i.e., essentially no adjustment) to a reduction of 2.88 percentage points in Pennsylvania and an increase of 2.53 for California. In addition, the standard errors associated with the adjusted rates are almost all larger than the corresponding measures for the State-reported rates.

Given the large samples on which these estimates are based, we can regard the ratio of each adjustment to its standard error as being (asymptotically) a unit normal variable. Hence, we can test the overall significance of the adjustments using a chi-squared statistic with 50 degrees of freedom. Performing this test yields the conclusion that the adjustments are, overall, reliably different from zero. In other words, the statistical procedure developed as part of this analysis does produce adjusted error rates that are reliably different from the State-reported error rates.

We next ask, "For which States is the difference between the reported and adjusted payment error rates different from zero?" To determine this, we examine the significance of the individual adjustments. As shown in Exhibit 4.8, the magnitude of the adjustments are such that for 15 States (i.e., 30 percent of the total) the difference between the reported and adjusted error rates is reliably different from zero. Arizona, California, Colorado, Massachusetts, Michigan, Ohio, and South Carolina receive positive adjustments (i.e., their error rate would be higher than reported if they had caseload and socioeconomic characteristics like the national average),

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EXHIBIT 4.8

Comparison of FY 84 State Reported Payment Error Rates to Adjusted Error Rates

State	State-Reported Error Rates		Adjusted Error Rates		Difference	
	Error Rate	Standard Error	Error Rate	Standard Error	(Adjusted-Reported)	t
Alabama	8.01	0.45	7.67	0.55	-0.34	-1.08
Alaska	9.34	1.40	10.70	2.62	1.36	0.61
Arizona	9.58	0.49	10.99	0.73	1.41***	2.61
Arkansas	9.55	0.70	7.79	0.77	-1.76***	-5.49
California	6.85	0.48	9.38	0.91	2.53***	3.27
Colorado	8.71	0.57	10.41	0.82	1.70***	2.88
Connecticut	7.01	0.62	8.36	0.96	1.35	1.84
Delaware	6.57	1.00	7.68	1.66	1.11	0.84
District of Columbia	8.91	0.91	6.27	1.38	-2.64***	-2.54
Florida	7.69	0.44	8.12	0.62	0.43	0.98
Georgia	9.42	0.67	10.24	0.94	0.82	1.24
Hawaii	4.11	0.57	4.13	1.00	0.02	0.02
Idaho	7.19	0.88	6.87	1.09	-0.32	-0.50
Illinois	a	a	--	--	--	--
Indiana	8.51	0.57	8.41	0.71	-0.10	-0.24
Iowa	8.22	0.66	8.30	0.80	0.08	0.18
Kansas	6.71	0.65	6.64	0.77	-0.07	-0.17
Kentucky	8.91	0.54	9.02	0.71	0.11	0.24
Louisiana	10.05	0.72	9.90	1.05	-0.15	-0.20
Maine	6.29	0.63	6.03	0.85	-0.26	-0.46
Maryland	6.68	0.61	6.32	0.90	-0.36	-0.54
Massachusetts	9.09	0.75	11.34	1.26	2.25**	2.22
Michigan	6.22	0.42	7.37	0.64	1.15**	2.38
Minnesota	8.61	0.66	8.63	0.83	0.02	0.04
Mississippi	8.19	0.64	7.97	0.74	-0.22	-0.59
Missorui	6.20	0.37	5.41	0.43	-0.79***	-3.61
Montana	8.43	0.83	8.95	1.16	0.52	0.64
Nebraska	8.64	0.70	7.51	0.76	-1.13***	-3.82

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EXHIBIT 4.8

Comparison of FY 84 State Reported Payment Error Rates
to Adjusted Error Rates

State	State-Reported Error Rates		Adjusted Error Rates		Difference	t
	Error Rate	Standard Error	Error Rate	Standard Error	(Adjusted-Reported)	
Nevada	2.26	0.54	2.67	1.17	0.41	0.40
New Hamphsire	8.31	1.00	8.64	1.31	0.33	0.63
New Jersey	7.26	0.46	7.75	0.61	0.49	1.22
New Mexico	10.25	0.58	10.33	0.72	0.08	0.19
New York	9.15	0.70	9.28	1.27	0.13	0.12
North Carolina	5.31	0.52	4.83	0.58	-0.48	-1.87
North Dakota	6.31	1.10	3.87	1.11	-2.44***	-16.41
Ohio	7.12	0.44	7.88	0.57	0.76**	2.10
Oklahoma	6.53	0.54	6.26	0.61	-0.27	-0.95
Oregon	7.70	0.99	6.20	0.84	-1.50***	-2.86
Pennsylvania	10.17	0.76	7.29	0.78	-2.88***	-16.41
Rhode Island	7.23	0.60	7.43	0.79	0.20	0.39
South Carolina	7.97	0.53	9.44	0.70	1.47***	3.21
South Dakota	3.63	0.62	3.48	0.69	-0.15	-0.50
Tennessee	5.82	0.53	5.71	0.71	-0.11	-0.23
Texas	7.15	0.63	7.13	0.68	-0.02	-0.08
Utah	9.64	1.03	8.82	1.42	-0.82	-0.84
Vermont	8.99	0.92	8.07	0.95	-0.92***	-3.88
Virginia	6.56	0.61	5.82	0.85	-0.74	-1.25
Washington	9.18	0.49	9.75	0.68	0.57	1.21
West Virginia	6.08	0.57	6.58	0.75	0.50	1.03
Wisconsin	8.32	0.43	8.44	0.58	0.12	0.31
Wyoming	9.01	1.40	8.46	1.47	-0.55	-1.23

a. Illinois was involved in a demonstration during FY84. Thus, its error rates are not comparable to those of other states

** Significantly different at the .05 level.
*** Significantly different at the .01 level.

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whereas Arkansas, District of Columbia, Missouri, Nebraska, North Dakota, Oregon, Pennsylvania, and Vermont receive negative adjustments (i.e., their error rates would be lower than reported if they had characteristics like the national average).

The Source of the Adjustments: How do these adjustments come about? To better explicate them, Exhibit 4.9 presents the adjustments associated with the various caseload and socioeconomic characteristics for the two States having the largest adjustments in either direction -- California and Pennsylvania. For each of the five models described earlier, this table provides the adjustment to the State's raw sample mean attributable to each of the separate variables.41/ The direction of the relationship between each factor and the respective outcome measure is indicated by the sign in parentheses located next to the variable name.

For convenience, we have provided the total adjustments previously shown in Exhibit 4.6 (i.e., the difference between the reported and adjusted values). For the models that deal with the food stamp allotment and the incidence of ineligibility error and overpayment error, the sum of the individual adjustments is approximately equal to the total adjustment. Slight differences are due to the effects of rounding and weighting. For the two models that focus on the amount of error, the adjustments cannot be directly summed because the underlying equations are nonlinear (additivity in the log amount scale translates into multiplicative contributions in the amount scale).

Consider, for example, California. Beginning with the first model, its adjusted allotment amount is the same as the corresponding reported value. Even though its caseload differs on the characteristics included in this model, the effects are offsetting to the point that the net difference is zero. State error rates reflect a complex interaction between a number of

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41/The adjustments were calculated by substituting into the equations the value of each State's mean on each of the specified characteristics.

EXHIBIT 4.9

Adjustments to State Sample Means Due to Individual Caseload and Socioeconomic Characteristics

Allotment ($)	California	Pennsylvania
Total Earned Income (-)	-7.9	-3.9
Medical Deductions (+)	+0.3	+0.02
Dependent Care Deductions (+)	+0.1	+0.06
Amount of AFDC Benefits (-)	+46.0	-0.5
Amount of Other Unearned Income (-)	-21.4	+5.3
Number of Case Members (+)	-14.3	+6.7
Shelter Costs (+)	-2.5	-0.5
Total Adjustment*	0.0	+$7.00

Incidence of Overpayment (%)	California	Pennsylvania
Population density (+)	-0.7	-2.0
True Presence of Earnings (+)	+0.3	+0.2
Number of Deductions (+)	+0.6	0.0
Number of Persons Receiving Institutional Unearned Income (+)	+0.8	+0.1
Receipt of AFDC (+)	-0.5	0.0
Number of Persons Aged 18-59 (+)	-0.3	-0.1
Total Adjustment	+0.6%	-1.4%

Amount of Overpayment ($)	California	Pennsylvania
Total Earned Income (-)	-0.02	-0.01
Amount of AFDC Benefits (-)	+0.02	-0.002
Amount of Other Unearned Income (-)	-0.06	+0.014
Number of Case Members (+)	-0.04	+0.016
Total Adjustment**	+$4.90	-$0.60

Incidence of Ineligibility (%)	California	Pennsylvania
Population Density (+)	-0.4	-1.2
Amount of Wage Income (+)	+0.2	0.0
Receipt of AFDC (-)	+0.6	0.0
Number of Persons Receiving SSI (-)	-0.3	0.0
Number of Persons Receiving Institutional Unearned Income (+)	+0.4	0.0
Number of Persons Aged 18-59 (+)	0.0	0.0
True Presence of Liquid Resources (+)	0.0	0.0
True Presence of Real Property (+)	+0.1	-1.6
True Presence of Vehicles (+)	0.0	0.0
Total Adjustment	+0.8%	-2.4%

Amount of Ineligibility	California	Pennsylvania
Total Earned Income (-)	-0.04	-0.02
Amount of AFDC Benefits (-)	+0.22	-0.003
Amount of Other Unearned Income (-)	-0.16	+0.04
Number of Case Members (+)	-0.08	+0.04
Total Adjustment**	$25.80	$12.40

*Adjustments from Exhibit 4.6

** Individual adjustments are not additive because the variables contribute multiplicatively.

factors commonly thought to be beyond the control of State and local managers. States vary on a number of dimensions, some of which tend to increase error rates while others result in lower rates. In most States, the factors that make the caseload more difficult to manage are balanced by other factors that make the caseload easier.

For example, California's caseload differs from the national average in a number of ways. For earned income (which is negatively related to benefit amount) the value of -7.9 means that California's caseload is below the national average on this characteristic and, if it were more similar to the national average, its average benefit would have been about $8.00 less than the actual California average (see Exhibit 4.10). Similarly, California provides much larger AFDC benefits. If its caseload received AFDC benefits more like the national average, California's average food stamp allotment would have been about $46 higher per month than it actually was in FY 84. The other adjustments work in a comparable manner, but because the adjustments work in both directions, the net effect is zero.

The characteristics of the caseload in Pennsylvania, on the other hand, also differs from the national average; but here the net effect is to increase the average food stamp allotment by $7.00.

Moving to the second model, the incidence of overpayment error, we see that the direction of the relationship is positive for all of the included caseload and socioeconomic characteristics. According to this model, States that are more urbanized or have caseloads with a greater proportion of earners, more deductions, more recipients of AFDC or other types of unearned income, and more adults are expected to have a higher probability of overpayment error. Because California has a caseload with less than average earnings and deductions and fewer recipients of institutional unearned income, its incidence of overpayment error is less than it would have been if it had a caseload similar to the national average (hence, the upward adjustment). Similarly, being more urbanized, having a caseload with a higher than average proportion of AFDC recipients and typically more adults tends to result in downward adjustments. Overall, California would be expected to have an incidence of overpayment error about 0.6 percent higher if its caseload were similar to the national average. Again, the situation in Pennsylvania is much different. Largely as a

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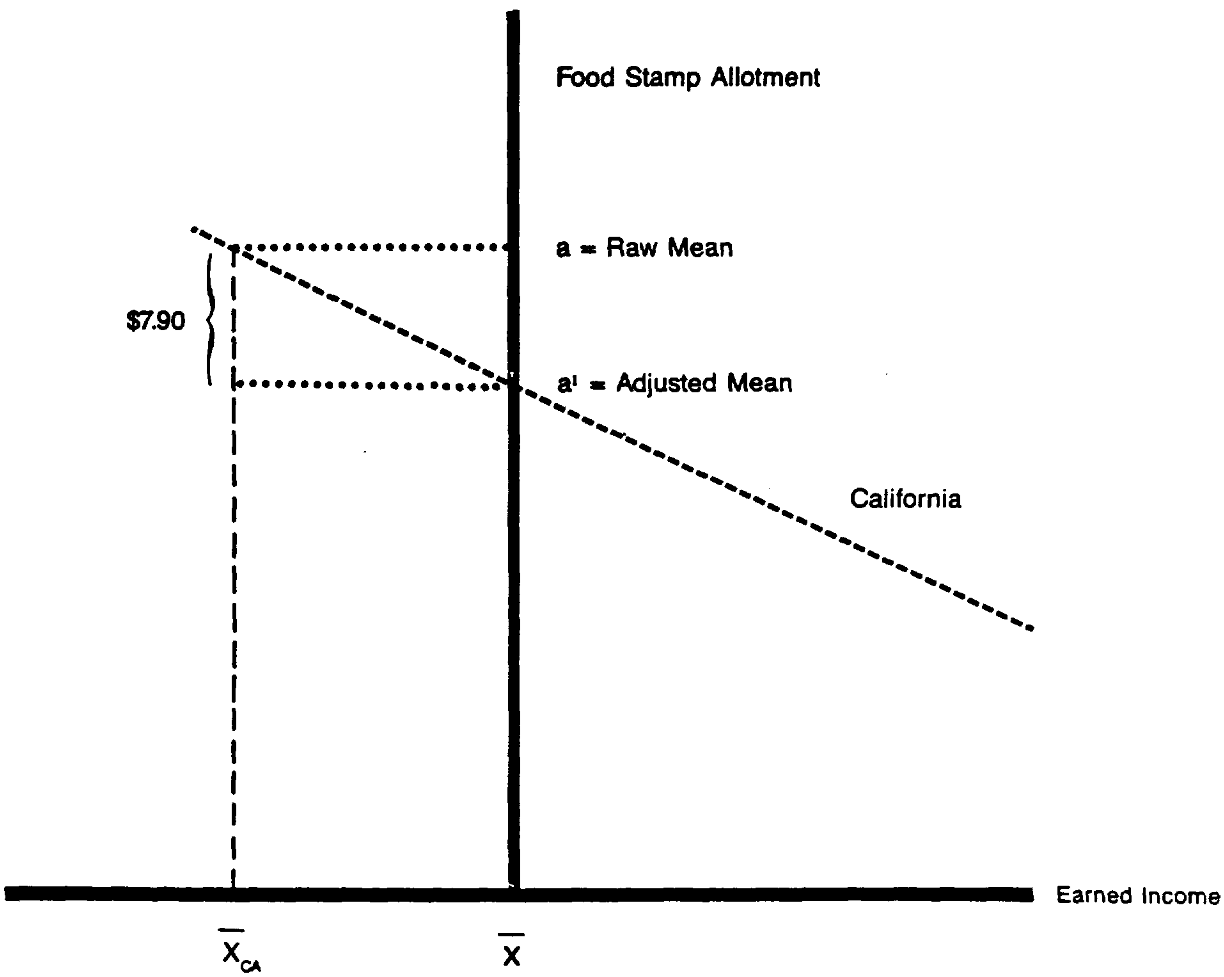
EXHIBIT 4.10
Diagrammatic Example of an Adjustment Effect*



*Assumes all other variables are at their national means.

result of its being considerably more urbanized than California, would be expected to have an incidence rate that is about 1.4 percent lower if it were more similar to the national average.

The third model, the amount of overpayment, has a different form than the two models previously discussed. Here, the caseload characteristics are related to the size of the overpayment error in a multiplicative manner, i.e., the sum of the adjustment effects exponentially increases the size of the overpayment. Otherwise, the interpretation of the importance of particular factors is essentially the same as the other models. However, the direction of the effects are different. Caseloads with higher earnings, AFDC benefits, and other unearned income would be expected to have, all other things being the same, smaller average overpayments. Presumably, this is because these same households also receive smaller allotments to begin with. As noted earlier, the magnitude of a household's overpayment (should there be one) is related to the size of its food stamp benefit.

With regard to the amount of an overpayment error, again the effects are such that California and Pennsylvania receive much different adjustments; California increases by almost $5.00 and Pennsylvania decreases by about $0.60. For the most part, the difference is due to the effect of AFDC benefits on the amount of an overpayment error.

The role that the level of AFDC benefits can play in explaining variation in food stamp error rates is illustrated by these results. In a special analysis of this interaction, it was shown that taking AFDC payment standards into account as an error rate adjustment factor would increase error rates in 37 States and lower error rates in fifteen42/. For some States, as in the example of California, exceptionally high or low AFDC benefits can generate an important factor adjustment to components of the payment error rate. As with all of the other factors found to be significant individually, however, this factor may be largely offset by other factors contributing opposing adjustments.

42/See Burstein, Nancy, Marie Hojnacki and Kaye Husbands "Impact of AFDC Payments on Food Stamp Payment Error Rates," Abt Associates, Inc., Forthcoming.

The remaining two models, the incidence and amount of ineligibility error, can be interpreted in a similar fashion. Pennsylvania's higher than average population density and real property assets yield a large downward adjustment in the incidence model, whereas California experiences a relatively small net upward adjustment due to offsetting effects from the individual factors. In the amount model, both States receive upward adjustments, but because of the effect of AFDC benefits in California, its adjustment is about twice as large as that for Pennsylvania.

These two examples illustrate that the individual factors identified in this analysis affect error rates in complex ways; the individual factors frequently have opposite effects and tend to offset each other. States vary on a number of dimensions, some of which result in higher error rates while others result in lower error rates. In most States, the factors that make the caseload more difficult to manage are balanced by other factors that make the caseload easier.

How Important Are The Adjustments?

The size of the adjustments ranges from -2.88 to +2.53 percentage points with an average of about 0.8 percentage points. The distribution of adjustments is as follows:

Adjustments	No. of States
-3.00 to -2.51	2
-2.50 to -2.01	1
-2.00 to -1.51	1
-1.50 to -1.01	2
-1.00 to -0.51	5
-0.50 to -0.01	13
0 to +0.49	12
0.50 to 0.99	5
1.00 to 1.49	6
1.50 to 1.99	1
2.00 to 2.49	1
2.50 to 2.99	1

If the adjustments were applied to a 5 percent general threshold (i.e., that currently in effect rather than the more complex threshold in effect in 1984), the highest threshold would be 7.9, and the lowest 2.5. Alternatively, if we keep the same adjustment structure but set the lowest threshold at 5 percent, the highest threshold would be 10.3 percent. It is interesting to note that these adjustments are much larger than

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those proposed under H.R. 1279 and H.R. 2621, both of which produce maximum threshold adjustments of about one percentage point.

The average reported error rate is approximately 7.7 percent and the average size of a State's adjustment is 0.8 percent. Therefore, on average, the adjustments represent an increment equal to about a tenth of the average State's reported error rate. Naturally, this varies. The adjustment is more than three-tenths of the error rate for three States, and more than two-tenths for another six.

Adjustments of this magnitude can have a substantial effect upon a State's liability for erroneous payments under current law. The liabilities for 22 States would not be affected by the adjustments; but, liabilities would be reduced for 16 States, and increased for 12. Any change in liabilities is substantial in dollar terms: under existing law the minimum change has to be 5 percent of the federal share of a State's administrative costs. Some of the changes would be quite large: for five States, the adjustment would add liabilities of 20-25 percent of their federal administrative costs; two would have reductions in liabilities of similar magnitude.

Overall, these figures indicate that the adjustments resulting from the modeling procedure are important. They are much bigger than the ones suggested in previous legislative proposals, and they could affect a substantial proportion of federal reimbursements in several States.

In fact, the adjusted error rates do vary slightly more than the reported error rates, as evident in the following figures:

	Reported Error Rates	Adjusted Error Rates
Mean	7.7	7.7
Minimum	2.3	2.7
Maximum	10.3	11.6
Range	8.0	8.9
Standard deviation	1.7	2.0
Coefficient of variation	0.22	0.26

These summaries imply that there are substantial differences in the effectiveness with which States control errors, even after we take into account (as best we can) the effect of important external factors.

In the next, and final chapter, we examine the extent to which the results described here are sensitive to slight changes in the specification of our model and to differences from year to year in the QC data.

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V. AN EXAMINATION OF THE SENSITIVITY OF THE ANALYTIC RESULTS

In Chapter I we specified six criteria that an adjustment procedure should meet in order to be acceptable, viz.,

1. The adjustment should be technically sound and defensible, conforming to generally accepted statistical standards.

2. States with comparable circumstances should have roughly the same adjustment.

3. The basis for the adjustments should be understandable to program managers.

4. The adjusted error rates should be meaningfully different from those derived under the current system.

5. The adjustment should not fluctuate dramatically from year to year unless the operating environment changes markedly.

6. The adjustment procedure should be reasonably robust--the adjustments should be relatively insensitive to minor changes in the factors used to calculate the adjustments.

The results presented in the previous chapter conform to generally accepted statistical standards and will produce (by virtue of the form of the model used) adjustments of the same magnitude for two States that have, an average, comparable caseload characteristics. Although the way in which the adjustments come about for a particular State is relatively complex (because of the multiple models and the use of a non-linear relationship for two of the five models), the number of factors used is small enough to provide appropriate signals to program managers. Finally, the adjusted error rates are reliably different from the State reported error rates for 30 percent of the States (i.e., 15 out of 50 States). The size of the adjustments are quite large; on average, error rates are equal to about 8 percent and the adjustments range from almost -3 percent to +2.5 percent.

Despite these findings, we are, at this time, hesitant to recommend the use of the statistical models described in Chapter IV for the purpose of actually adjusting State error rates. The adjustments are, as will be shown in this chapter, reasonably sensitive to the choice of variables that are included in the models especially the exclusion of an important measure of caseload and socioeconomic characteristics. In addition, the magnitude and direction of the adjustments are quite sensitive to changes in the QC data from year to year.

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As a result, State adjustments can shift dramatically; one year providing a benefit and the next year providing a liability.

The year to year changes, although potentially bothersome for State administrators, is largely due to sampling variability that affects even current procedures for calculating State error rates. The complexity of the adjustment procedures will just make these differences seem more arbitrary and may exacerbate the current perception of a lack of fairness in the QC system.

The more troublesome problem we encountered is that the exclusion of an important explanatory variable yields adjustments that are substantially different for a large number of States. Because a class of potentially important factors -- measures of caseload dynamics -- could not be included in this analysis (due to data limitations) proceeding with the models presently available might entail compensating States on the basis of a seriously inaccurate picture of the caseload and socioeconomic characteristics that make controlling payment errors more, or less, difficult. Until further analysis is done, we cannot recommend such a major revision to the Food Stamp Program with its accompanying fiscal consequences for States.

Finally, compared to two recently introduced legislative proposals, the models discussed in Chapter IV do a much better job of accounting for variation in the incidence and amount of payment error. If we consider the legislative proposals to reflect the "conventional wisdom" regarding factors which make it more or less difficult to control erroneous payments, it is clear that compensating States for the different problems they face is far more complex than originally anticipated. The empirical models yield adjustments that are substantially different, both in magnitude and direction, from those associated with the legislative proposals. As a consequence, our concerns about the feasibility of proceeding with an adjustment procedure at this time should not be used to provide support for such heuristic adjustments.

Comparison With Legislative Proposals

The first alternatives we examined were the two recently introduced legislative proposals H.R. 1279 and H.R. 2621 (previously discussed in Chapter I). The question is, "How well do our empirically derived statistical models compare

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with adjustment models based on factors generally considered to be influential?" To test this we used the five models described in Chapter IV (i.e., the incidence and amount of overpayments to eligibles and ineligibles respectively and the magnitude of the food stamp allotment) but replaced our variables with those stipulated in each of the two proposals. The models were then re-estimated to compute the adjusted State means needed to calculate adjusted State error rate as discussed in Chapter III.

Exhibit 5.1 depicts the result of these comparisons. The second column provides the adjustments associated with the statistical models described in Chapter IV. The third and fourth columns provide the adjustments associated with the same types of models based on the factors included in H.R. 1279 and H.R. 2621, respectively. Disregarding direction, the three alternatives produce adjustments of approximately the same magnitude; i.e., the average adjustment ranges from 0.72 percent to 0.78 percent across the three alternatives. However, individual States fare quite differently under the alternative specifications. The correlation between our original adjustments and those associated with the H.R. 2621 factors (i.e., comparing columns 2 and 3 of Exhibit 5.1) is only 0.378. A similar comparison using the factors specified in H.R. 1279 yields a correlation of 0.537.

Another perspective on the consistency of the adjustments is provided by considering the absolute magnitude of the difference between them. To do this, we compare our original adjustments to those resulting from the models based upon the two legislative proposals, and count the number of differences greater than 1 percentage point and the number between 0.5 and 1 percent. In the current liability system, a 1-point adjustment would always affect the liability of a State that is over the liability threshold.43/ A half-percent adjustment

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43/The current system involves a "step function," in which the liability changes at integer values of the error rate. Thus, a State with an error rate of 7.9 percent has the same proportionate liability as one with a 7.1 percent error rate, but a State with an error rate of 8.0 percent has a higher liability.

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EXHIBIT 5.1
Comparison of FY 84 State Adjusted Payment Error Rates
to Adjustments Associated with Two Legislative Proposals

State	Original Statistical Model Adjustments	Adjustments based on H.R. 2621 Factors	Adjustments based on H.R. 1279 Factors
Alabama	-0.34	0.05	-0.13
Alaska	1.36	1.24	1.35
Arizona	1.41	1.25	0.02
Arkansas	-1.76	-0.16	-0.41
California	2.53	2.17	1.85
Colorado	1.70	1.38	1.43
Connecticut	1.35	-0.35	0.81
Delaware	1.11	-0.28	0.18
District of Columbia	-2.64	-2.16	-3.08
Florida	0.43	-0.14	0.26
Georgia	0.82	0.04	-0.73
Hawaii	0.02	-0.23	0.90
Idaho	-0.32	0.48	-0.31
Illinois[a]	--	--	--
Indiana	-0.10	-0.57	-0.42
Iowa	0.08	0.33	0.35
Kansas	-0.07	0.04	0.27
Kentucky	0.11	0.51	0.17
Louisiana	-0.15	0.70	0.44
Maine	-0.26	0.76	0.56
Maryland	-0.36	-0.37	-0.65
Massachusetts	2.25	0.62	1.02
Michigan	1.15	0.35	1.07
Minnesota	0.02	0.37	0.95
Mississippi	-0.22	0.81	-0.26
Missouri	-0.79	-0.48	-0.60
Montana	0.52	1.41	0.97
Nebraska	-1.13	-0.71	-0.06
Nevada	0.41	0.90	0.55
New Hampshire	0.33	1.60	1.60
New Jersey	0.49	0.23	0.10
New Mexico	0.08	1.87	0.70
New York	0.13	-0.27	0.55
North Carolina	-0.48	0.55	0.34
North Dakota	-2.44	0.13	-0.24
Ohio	0.76	0.12	1.04
Oklahoma	-0.27	0.28	0.16
Oregon	-1.50	-1.39	-1.87
Pennsylvania	-2.88	0.20	-0.08
Rhode Island	0.20	-0.39	1.49
South Carolina	1.47	2.31	0.67
South Dakota	-0.15	0.61	0.11

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EXHIBIT 5.1
Comparison of FY 84 State Adjusted Payment Error Rates
to Adjustments Associated with Two Legislative Proposals

State	Original Statistical Model Adjustments	Adjustments based on H.R. 2621 Factors	Adjustments based on H.R. 1279 Factors
Tennessee	-0.11	0.43	0.36
Texas	-0.02	0.16	0.14
Utah	-0.82	-0.39	-0.19
Vermont	-0.92	1.34	1.39
Virginia	-0.74	1.46	1.08
Washington	-0.57	1.28	1.86
West Virginia	0.50	1.38	1.16
Wisconsin	0.12	1.40	0.95
Wyoming	-0.55	0.42	-0.02

a. Illinois was involved in a demonstration during FY84, therefore, its error rates are not comparable to those of other States.

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would be expected to affect the liability of about half of those States (i.e., we would expect about half of the States to be pushed over the next error rate increment). A smaller adjustment would be expected to affect the liabilities for less than half of the States to which it was applied.

By this criterion, the difference between the various adjustment procedures are quite important. The adjustments based on the H.R. 2621 variables differ from our original adjustments by at least 1 percent in 14 States, and by half a percent in another 15 States. The model based on the H.R. 1279 variables yields 1-percent differences for 12 States, and half-percent differences for 14. In both cases, then, adjustment differences are potentially important for about 20 States (i.e., 14 + 15/2 = 21, 12 + 14/2 = 19).

In several instances, the size and direction of the adjustments are dramatically different. For example, Pennsylvania, which received a downward adjustment of almost 3 percent under our original statistical model, would receive a slight upward adjustment if the H.R. 2621 variables had been used. Similarly, Massachusetts, which was adjusted upward by 2.25 percent under our original model specification, would be adjusted upward by only 0.62 percent using the H.R. 2621 variables.

Alternative Model Specifications

In addition to comparing our model to the two legislative proposals, we also examined the sensitivity of the adjustments to other changes in the specification of the five models that comprise our adjustment procedure. Exhibit 5.2 provides the result of this comparison for six alternatives (during the development of the statistical models many more alternatives were examined--for clarity, we have selected only a small number for presentation purposes). In each instance, slight modifications are made to the models with all other aspects being held constant. Alternative #1 alters the specification of earned income in the two incidence models, alternative #2 substitutes a measure of true earnings for reported earnings in the allotment and error amount models, alternatives #3 and #5 alter the way in which household size is measured, alternative #4 replaces the various measures of earned income used in the original five models with the number of persons in the household that have earned income, and finally alternative #6 excludes population density from the two incidence models.

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EXHIBIT 5.2

Adjustments to State Payment Error Rates Under Six Alternative Model Specificiations

State	Original Model	Alternative #1	Alternative #2	Alternative #3	Alternative #4	Alternative #5	Alternative #6
Alabama	-0.34	-0.19	-0.69	-0.25	-0.65	-1.80	-0.77
Alaska	1.36	1.11	0.48	1.70	0.73	1.06	0.79
Arizona	1.41	1.44	0.87	1.55	0.68	-0.69	0.97
Arkansas	-1.76	-1.61	-1.64	-1.79	-1.64	-3.10	-2.18
California	2.53	2.40	2.96	2.53	3.53	8.70	2.70
Colorado	1.70	1.70	1.66	1.51	1.62	1.45	1.70
Connecticut	1.35	1.35	1.44	1.05	1.86	3.43	1.26
Delaware	1.11	1.30	0.51	1.15	0.83	0.53	0.93
District of Columbia	-2.64	-2.59	-2.71	-2.55	-2.77	-2.75	2.41
Florida	0.43	0.53	0.53	-0.02	0.45	-0.52	0.12
Georgia	0.82	1.13	0.57	0.86	0.66	-1.34	0.55
Hawaii	-0.02	0.17	0.16	-0.12	0.49	0.12	-0.14
Idaho	-0.32	-0.32	-0.62	-0.18	-0.69	-1.36	-0.85
Indiana	-0.10	-0.13	-0.13	0.11	-0.31	-1.35	-0.41
Iowa	0.08	0.11	-0.10	0.11	0.001	0.39	-0.39
Kansas	-0.07	-0.10	-0.24	-0.18	-0.22	0.07	-0.38
Kentucky	0.11	0.11	-0.14	0.59	-0.35	-1.75	-0.23
Louisiana	-0.15	-0.19	0.54	-0.12	0.26	-1.60	-0.55
Maine	-0.26	-0.32	-0.36	-0.26	-0.44	-0.24	-0.76
Maryland	-0.36	-0.36	-0.58	-0.29	-0.71	-0.62	1.91
Massachusetts	2.25	2.21	2.28	1.84	2.33	4.29	2.65
Michigan	1.15	0.79	1.00	1.08	0.60	2.06	1.35
Minnesota	0.02	-0.04	0.27	-0.07	0.40	1.47	-0.14
Mississippi	-0.22	-0.03	-0.56	-0.34	-0.56	-1.87	-0.74
Missouri	-0.79	-0.83	-1.00	-0.83	-1.04	-1.57	-0.58
Montana	0.52	0.73	0.04	1.08	0.20	-0.52	0.27
Nebraska	-1.13	-1.01	-1.05	-1.09	-0.85	-1.32	-1.40
Nevada	0.41	0.32	0.49	0.24	0.38	-0.06	-0.14
New Hampshire	0.33	0.38	0.56	0.07	0.68	0.21	-0.15
New Jersey	0.49	0.41	0.55	0.29	0.51	0.23	1.81
New Mexico	0.08	0.19	0.59	0.25	0.50	-2.07	-0.53
New York	0.13	-0.07	-0.32	-0.04	-0.32	0.25	0.83
North Carolina	-0.48	-0.26	-0.32	-0.52	-0.13	-1.08	-0.84
North Dakota	-2.44	-2.40	-2.23	-2.63	-2.38	-2.54	-2.89
Ohio	0.76	0.68	0.67	0.86	0.60	-0.13	0.76
Oklahoma	-0.27	-0.27	-0.15	-0.45	-0.18	-1.25	-0.64
Oregon	-1.50	-1.41	-1.36	-1.78	-1.23	-1.93	-1.86
Pennsylvania	-2.88	-3.01	-2.79	-2.66	-2.93	-2.74	-1.53
Rhode Island	0.02	0.16	-1.40	-0.06	0.71	0.63	0.16
South Carolina	1.47	1.70	1.63	1.52	1.65	-1.66	1.03
South Dakota	-0.15	-0.05	-0.32	-0.10	-0.27	-0.13	0.47
Tennessee	-0.11	0.01	-0.07	0.17	-0.01	-1.37	-0.42
Texas	-0.02	0.12	0.27	-0.08	0.22	-0.57	-0.29
Utah	-0.82	-0.73	-0.30	-0.82	-0.26	-2.25	-0.33
Vermont	-0.92	-0.84	-0.64	-0.91	-0.29	-0.50	-1.30
Virginia	-0.74	-0.60	-0.49	-0.60	-0.40	-1.65	-0.95
Washington	0.57	0.54	0.54	0.57	0.72	0.86	0.08
West Virginia	0.50	0.38	0.41	1.00	0.33	-0.49	0.08
Wisconsin	0.12	0.17	0.30	0.25	0.78	4.74	0.40
Wyoming	-0.55	-0.43	-0.60	-0.47	-0.53	-4.27	-1.00

Alternative #1: Substitutes total earned income for true presence of income and total wages in the two incidence models.

Alternative #2: Substitutes measure of true earnings for reported earnings in allotment and error amount models.

Alternative #3: Substitutes total number of household members for number of adults in the two incidence models.

Alternative #4: Substitutes number of persons with earnings for amounts and presence of earnings in all five models.

Alternative #5: Substitutes number of persons aged 18-59 for total household members in allotment and two error amount models.

Alternative $6: Excludes population density from the two incidence models.

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For the most part, the equations used to calculate the adjustments provided in this table performed equally well, i.e., the regression coefficients were generally significant, and the explanatory power of the models was roughly the same.44/ A comparison of the adjustments, however, yields an interesting picture.

To begin with, consider what happens when we alter how we measure the effect of differences in the extent to which a State's caseload is characterized by earnings. To do this, we compare the adjustments produced under alternatives #1, #2 and #4 to those of our original adjustment models. The general pattern of the adjustments is quite similar, but some important differences still exist. The correlations between the original adjustments and the three alternatives are 0.99, 0.95, and 0.95, respectively. However, although differences between the adjustments are generally small, only the first alternative produces no adjustments that differ from the original set by more than 0.5 percent. Alternative #2 yields five half-percent differences, and alternative #4 yields eight; each alternative also produces one adjustment of a least one percent. Thus, for a few States, these very small differences in defining the prevalence of earned income could make important differences in their liability for erroneous payments.

Moving to alternatives #3 and #5, we see the result of changing how we measure the effect of differences in the size of client households on the magnitude and direction of the adjustments. Instead of using the total number of case members, these alternatives employ the use of the number of persons between the ages of 18 and 59. Here the picture is somewhat different -- the correlation between the original adjustments and those produced under alternative #3 is 0.98, but the correlation between the original adjustments and those associated with alternative #5 is 0.69. In the first instance, we changed only

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44/The explanatory power of the various models used to calculate the adjustments (i.e., the value of R^2) was, for the most part, very consistent across the different options. For example, the R^2 value: for the incidence of overpayment error ranged from 0.03 to 0.033; for the incidence of ineligibility error ranged from 0.02 to 0.028; for the amount of overpayment error ranged from 0.05 to 0.09; and, for the amount of ineligibility error ranged from 0.22 to 0.33.

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the two incidence models; in the second instance, we altered the specification in the two error amount models and the allotment equation. For the most part, the larger differences in the second situation are due to the effect of this change in specification on the allotment model. By using the number of adults (i.e., the number of potential wage earners) as the measure of household size, the model produces substantially different adjustments for those States where the proportion of cases with members under the age of 18 is large. This is typically the case for States with large numbers of AFDC recipients in their food stamp caseload. For such States, the differences in the size of the adjustments are quite large: ten States receive adjustments that differ by from 0.5 to 1.0 percent whereas twenty States receive adjustments that differ by more than one percent. In fact, six States exhibit changes in their adjustments in excess of two percent -- California, Connecticut, Massachusetts, New Mexico, Wisconsin and Wyoming. Under this alternative, a large number of States would be affected in a way that would result in important differences in the size of their liability.

The last and most important example, alternative #6, demonstrates the effect of simply excluding a key variable from the models. In this example, we have computed the adjustments with population density dropped from the two incidence models. This change produces adjustments that are fundamentally different from those estimated using the original model specifications. The correlation between the two sets of adjustments is 0.68, and a number of States are substantially affected by the change. For example, for nine States the direction of the adjustment changes, and for four States the magnitude of the difference exceeds one percent (the District of Columbia, 5 percent; Maryland, 1.6 percent; New Jersey, 1.3 percent; and Pennsylvania, 1.4 percent). Another nine States receive adjustments that differ by more than a half-percent. Again, because of the way liabilities are determined under current law, changes of this magnitude in the adjusted error rates could have substantial fiscal consequences for these States.

This last comparison is particularly important because it demonstrates the sensitivity of the adjustments to the exclusion of potentially influential variables. We know, for example, that at least one class of possibly important factors were not included in this analysis. Measures of caseload dynamics--the rates at which households enter or leave the program and the frequency of changes in household circumstances--were simply not available. Although it is

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impossible at this point to state what effect the inclusion of these variables would have had on the adjustments, we do know that this factor was considered to be important enough to be included in the legislative proposal recently introduced by as part of H.R. 2621. Anecdotal evidence from State and local program managers has also indicated that such changes are a major cause of payment errors. If this factor is indeed an important determinant of differences in the incidence and amount of payment errors, its exclusion could have significant consequences for at least some States.45/

Temporal Stability Of The Results

The potential for year-to-year variation in adjustment results also presents a problem. To be acceptable, an adjustment procedure should be relatively stable from one year to the next. Wide swings in the size or direction of error rate adjustments would probably raise serious questions about the fairness or usefulness of the whole adjustment process.

To examine this issue, we have run the models presented in Chapter IV against the FY 85 IQCS data and calculated adjusted error rates, as was done using the FY 84 data, with one difference. Because we were unable to link the FY 85 QC file to the Census data (the office code information needed to make the link was not available in time), the models discussed in this section do not include population density in the two incidence equations. For comparison purposes, the results discussed below for FY 84 also omit this variable. The basic conclusion about year-to-year variation, however, is not affected by this departure from the model results reported earlier.46/

Exhibit 5.3 provides, by State for FY 84 and FY 85, the reported payment error rate, the adjusted error rate, and the

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45/The legislative proposal used State-level measures which are available. To include this factor in our models, however, we needed office-level and household-level data which were not available.

46/It should also be noted that for most offices the measure of population density used would have remained unchanged from FY84 to FY85 anyway (it was based on 1980 Census information). The only changes that would have occurred would have been due to changes in local office boundaries.

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EXHIBIT 5.3

Comparison of Adjusted and Reported Payment Error Rates for FY 84 and FY 85

State	Fiscal Year 1984[a] Reported Error Rate	Fiscal Year 1984[a] Adjusted Error Rate	Fiscal Year 1984[a] Difference	Fiscal Year 1985 Reported Error Rate	Fiscal Year 1985 Adjusted Error Rate	Fiscal Year 1985 Difference
Alabama	8.01	7.24	-0.77	11.35	9.91	-1.44***
Alaska	9.34	10.13	0.79	12.07	13.37	1.30
Arizona	9.58	10.55	0.97	8.75	7.82	-0.93***
Arkansas	9.55	7.37	-2.18***	6.51	6.58	0.07
California	6.85	9.55	2.70***	6.61	10.03	3.42***
Colorado	8.71	10.41	1.70***	7.93	7.86	-0.07
Connecticut	7.01	8.27	1.26	6.97	8.90	1.93***
Delaware	6.57	7.49	0.93	7.19	8.68	1.49
District of Columbia	8.91	11.32	2.41	8.37	11.53	3.16**
Florida	7.69	7.81	0.12	6.51	6.55	0.04
Georgia	9.42	9.97	0.55	10.71	9.50	-1.21***
Hawaii	4.11	3.97	-0.14	3.95	3.64	-0.30
Idaho	7.19	6.34	-0.85	3.86	2.67	-1.19***
Illinois	b	--	--	--	--	--
Indiana	8.51	8.10	-0.41	10.26	9.87	-0.36
Iowa	8.22	7.83	-0.39	8.36	7.70	-0.66
Kansas	6.71	6.34	-0.38	6.65	5.96	-0.69
Kentucky	8.91	8.68	-0.23	5.81	5.83	0.02
Louisiana	10.05	9.50	-0.55	9.11	8.31	-0.80
Maine	6.29	5.53	-0.76	7.63	6.79	-0.85
Maryland	6.68	8.59	1.91**	7.31	9.14	-1.83***
Massachusetts	9.09	11.74	2.65***	8.54	9.70	1.16
Michigan	6.22	7.57	1.35***	6.82	8.78	1.95***
Minnesota	8.61	8.47	-0.14	8.30	7.70	-0.60
Mississippi	8.19	7.45	-0.74	7.33	6.05	-1.28***
Missouri	6.20	5.62	-0.58**	5.64	4.67	-0.97***
Montana	8.43	8.70	0.27	7.33	6.80	-0.53
Nebraska	8.64	7.24	-1.40***	8.92	6.66	-2.26***
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
New Hampshire	8.31	8.16	-0.15	4.03	3.80	-0.23
New Jersey	7.26	9.07	1.81***	8.50	11.06	2.56***
New Mexico	10.25	9.72	-0.53	8.35	7.62	-0.73***
New York	9.15	9.98	0.83	6.44	8.79	2.35***
North Carolina	5.31	4.47	-0.84***	4.96	3.90	-1.06***
North Dakota	6.31	3.42	-2.89***	3.38	1.00	-2.38***
Ohio	7.12	7.88	0.76**	6.69	7.98	1.29***
Oklahoma	6.53	5.89	-0.64***	8.95	7.52	-1.43***
Oregon	7.70	5.86	-1.84***	9.05	7.55	-1.50***
Pennsylvania	10.17	8.64	-1.53***	8.64	6.23	-2.41***
Rhode Island	7.23	7.39	0.16	7.74	8.80	1.06**
South Carolina	7.97	9.00	1.03**	11.27	10.22	-1.05***
South Dakota	3.63	3.16	-0.47	3.12	1.62	-1.50***
Tennessee	5.82	5.40	-0.42	5.97	5.56	-0.41
Texas	7.15	6.86	-0.29	7.98	6.78	-1.20***
Utah	9.64	9.31	-0.33	7.50	7.60	0.09
Vermont	8.99	7.69	-1.30***	7.28	6.34	-0.94
Virginia	6.56	5.61	-0.95**	6.38	5.70	-0.68
Washington	9.18	9.26	0.08	8.77	9.76	0.99**
West Virginia	6.08	6.16	0.08	4.71	5.21	0.50
Wisconsin	8.32	8.72	0.40	7.93	9.23	1.30***
Wyoming	9.01	8.01	-1.00***	7.23	6.60	-0.63

a. Adjustments are estimated excluding population density.
b. Illinois was involved in a demonstration during FY84, therefore, its error rates are not comparable to those of other states

** Significantly different at the .05 level.
*** Significantly different at the .01 level.

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difference between the two estimates. Statistical significance is also indicated where appropriate. The correlation between the two sets of adjustments is not particularly high (i.e., 0.68), indicating a relatively large divergence between the adjustments in the two years. The number of States with statistically significant adjustments is also much different--19 are reliably different from zero in FY 84 47/, and 27 are reliably different in FY 85.

For individual States, the differences from year to year are quite large. In nineteen States the differences are between 0.5 and 1.0 percent, and for ten States the difference exceeds one percent. In some instances, the changes involve a substantial difference in both the magnitude and direction of the adjustment. For example, Arkansas from -2.18 to 0.07, Colorado from 1.70 to -0.07, Georgia from 0.55 to -1.21, Maryland from 1.91 to -1.83, Montana from 0.27 to -0.53, Nevada from -0.14 to 0.85 and South Carolina from 1.03 to -1.05. Changes of this sort would be particularly troublesome for States, because they would be expecting to have their error rates altered in one direction but would receive a totally different adjustment in an ensuing year. For other States, the adjustments do not change direction but differ by an amount that could represent a significant change in liability. For example, New York's adjustment increases by over 1.5 percent, which, under the existing liability system, would have increased its liability by 10 percent for FY85--approximately $12 million.

This apparently large instability from year to year raises the question, "What is the cause of these changes--is it differences in the model or in the data?" As demonstrated in Exhibit 5.4, the parameter estimates are reasonably stable, considering that these data come from independent samples. The absolute sizes of the coefficients do change, but most of the changes are small. The model for the amount of ineligibility error has the largest relative change between the two years, which is not surprising, given the infrequency with which this type of error occurs and the resulting sample sizes available for analysis.

47/This is different from the number reported in Chapter 4 because of the previously discussed change in model specification.

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EXHIBIT 5.4

Coefficients from Adjustment Models:
FY84 versus FY85

	FY 84	FY 85
Allotment		
Total Earned Income	-0.19	-0.17
Medical Deductions	0.17	0.12
Dependent Care Deductions	0.14	0.09
Amount of AFDC Benefits	-0.18	-0.15
Amount of Other Unearned Income	-0.22	-0.18
Number of Persons in case	48.70	49.38
Shelter Costs	0.04	0.05
Incidence of Overpayment		
True Presence of Income	0.05	0.11
Number of Deductions	0.05	0.02
Occurrences of Institutional Unearned Income	0.04	0.04
Receipt of AFDC	0.02	0.04
Number of Persons Aged 18-59	0.04	0.02
Amount of Overpayment		
Total Earned Income	-5.5E-4 *	-7.2E-4
Amount of AFDC Benefits	-7.1E-4	-13.5E-4
Amount of Other Unearned Income	-5.9E-4	-9.3E-4
Number of Persons in Case	0.12	0.19
Incidence of Ineligibility		
Amount of Wage Income	4.5E-5	3.9E-5
Receipt of AFDC	-0.02	-0.02
Occurrences of SSI	-0.02	-0.02
Occurrences of Institutional Unearned Income	0.02	0.01
Number of Persons Aged 18-59	8.0E-3	4.4E-3
True Presence of Liquid Resources	0.01	0.02
True Presence of Real Property	0.18	0.35
True Presence of Vehicles	0.32	0.05
Amount of Ineligibility		
Total Earned Income	-10.9E-4	-14.3E-4
Amount of AFDC Benefits	-8.4E-4	-17.4E-4
Amount of Other Unearned Income	-16.2E-4	-23.9E-4
Number of Persons in Case	0.26	0.47

*This is scientific notation; 5.5E-4 stands for 5.5×10^{-5}, i.e., 0.000055.

To examine the issue further, we evaluated the adjustments under two general alternatives: 1) holding the parameters of the models constant and calculating adjustments by varying the data (e.g., estimating adjustments using the FY84 models with the FY84 data and the FY85 data) and 2) holding the data constant and varying the parameters of the models (e.g., estimating adjustments using the FY84 data with both the FY84 and FY85 models). The results of these various tests were examined with regard to the correlation among the adjustments across the different alternatives. The results indicate that it is mainly differences in the data, rather than differences in the models, that cause the differing adjustments. It is not that State caseload characteristics are changing dramatically from year to year. Rather, differences in the characteristics of cases in the QC sample (which arise as a result of sampling variability), appear to be capable of causing important differences in the error rate adjustment.

In any event, it is clear that, at a minimum, there exists the strong possibility that year-to-year differences in the size and direction of the adjustments could be large enough to significantly alter States' liability for erroneous payments. Moreover, the uncertainty of the process could be such that the introduction of a formal adjustment procedure would only exacerbate the current debate over the fairness of the present system.

APPENDIX A

IQCS REVIEW SCHEDULE

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WORKSHEET FOR INTEGRATED AFDC, FOOD STAMPS AND MEDICAID QUALITY CONTROL REVIEWS

Integrated Review No. ______
Form Approved
OMB No. 0960-0176

PRIVACY ACT/PAPERWORK ACT NOTICE: This report is required under provisions of 45 CFR 205.40 (AFDC), 7 CFR 275.14 (Food Stamp) and 42 CFR 431.800 (Medicaid). This information is needed for the review of State performance in determining recipient eligibility. The information is used to determine State compliance and failure to report may result in a finding of non-compliance.

A. IDENTIFYING INFORMATION

PROGRAMS UNDER REVIEW

☐ AFDC ☐ ADULT	☐ FOOD STAMPS ☐ ACTIVE ☐ NEGATIVE	☐ MEDICAID ☐ AFDC ☐ AFDC RELATED ☐ SSI ☐ SSI RELATED NEEDY INDIVIDUAL UNDER 21

1 LOCAL AGENCY ______

2 CASE NAME ______

3 ADDRESS ______

4 PHONE NUMBER ______

5 DIRECTIONS TO LOCATE ______

	AFDC/ADULT	FOOD STAMPS	MEDICAID
6 CASE NUMBER(S)			
7 REVIEW NUMBER(S)			
8 REVIEW DATE MONTH			
9 DATE OF MOST RECENT OPENING CERTIFICATION		Date Application Received	
10 MOST RECENT ACTION			
a Date b Type			
11 CERTIFICATION PERIOD		from to	from to
12 PARTICIPATED DURING SAMPLE MONTH		☐ YES ☐ NO	
13 REC'D EXPEDITED SERVICE		☐ YES ☐ NO	
14 REVIEWER(S)			
15 DATE(S) ASSIGNED			
16 DATE OF CASE READING(S)			
17 DATE OF HOME VISIT(S)			
18 DATE(S) COMPLETED			
19 SUPERVISOR(S)			
20 DATE(S) CLEARED			

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B. PERSONS LIVING IN THE HOME

	NAME	BIRTHDATE	AGE	RELATIONSHIP OR SIGNIFICANCE	SOCIAL SECURITY NUMBER	AFDC/ADULT Recip	AFDC/ADULT Elig	FS Recip	MEDICAID Recip	MEDICAID Elig.	MEDICAID Serv Rec	MEDICAID TPL
1												
2												
3												
4												
5												
6												
7												
8												
9												
10												

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C. SIGNIFICANT PERSONS NOT LIVING IN THE HOME

	NAME	RELATIONSHIP OR SIGNIFICANCE	SOCIAL SECURITY NUMBER	ADDRESS	FINANCIAL SUPPORT	TPL RESOURCE
11						
12						
13						
14						
15						

D. REVIEW FINDINGS

AFDC/ADULT

GRANT AMOUNT ______

☐ AMOUNT CORRECT
☐ OVERPAYMENT
☐ UNDERPAYMENT
☐ INELIGIBLE

AMOUNT IN ERROR ______

NUMBER OF ELEMENTS IN ERROR ______

FOOD STAMPS

ALLOTMENT ______

☐ AMOUNT CORRECT
☐ OVERISSUANCE
☐ UNDERISSUANCE
☐ INELIGIBLE
☐ VALID NEGATIVE CASE
☐ INVALID NEGATIVE CASE

AMOUNT IN ERROR ______

MEDICAID

ELIGIBILITY STATUS
☐ ELIGIBLE
☐ LIABILITY UNDERSTATED
☐ LIABILITY OVERSTATED
☐ TOTALLY INELIGIBLE
☐ ELIGIBLE WITH INELIGIBLE MEMBER(S)
☐ LIABILITY UNDERSTATED WITH INELIGIBLE MEMBERS
☐ LIABILITY OVERSTATED WITH INELIGIBLE MEMBERS

INITIAL LIABILITY ERROR ______

NUMBER OF ELEMENTS IN ERROR ______

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
	BASIC PROGRAM REQUIREMENTS (100)					
110 AGE AND SCHOOL ATTENDANCE			1 2 3	1 2 3	1 2 3	1 2 3
120 RELATIONSHIP			1 2 3		1 2 3	
130 CITIZENSHIP AND ALIENAGE			1 2 3	1 2 3	1 2 3	1 2 3
140 RESIDENCY			1 2 3	1 2 3	1 2 3	1 2 3

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
150 LIVING ARRANGEMENT AND HOUSEHOLD COMPOSITION			1 2 3	1 2 3	1 2 3	1 2 3
160 WORK/WIN REGISTRATION			1 2 3	1 2 3		
161 EMPLOYMENT/JOB SEARCH			1 2 3	1 2 3		
170 SOCIAL SECURITY NUMBER			1 2 3	1 2 3	1 2 3	1 2 3

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			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
CATEGORICAL RELATEDNESS: 181 DEATH 182 INCAPACITY 183 CONTINUED ABSENCE 184 UNEMPLOYED PARENT			1 2 3		1 2 3	
185 BLINDNESS/ DISABILITY DETERMINATION 186 OTHER CATEGORICAL RELATEDNESS					1 2 3	1 2 3
CHILD SUPPORT PROGRAM: 191 ASSIGNMENT OF SUPPORT			1 2 3		1 2 3	
192 COOPERATION IN SUPPORT ACTIVITIES			1 2 3		1 2 3	

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
LIQUID RESOURCES: 211 BANK ACCOUNTS OR CASH ON HAND			1 2 3	1 2 3	1 2 3	1 2 3
212 NONRECURRING LUMP-SUM PAYMENTS				1 2 3		1 2 3
213 OTHER LIQUID ASSETS AND PERSONAL PROPERTY			1 2 3	1 2 3	1 2 3	1 2 3
NON-LIQUID RESOURCES: 221 REAL PROPERTY			1 2 3	1 2 3	1 2 3	1 2 3

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
222 VEHICLE			1 2 3	1 2 3	1 2 3	1 2 3
223 LIFE INSURANCE			1 2 3		1 2 3	1 2 3
224 OTHER NON-LIQUID RESOURCES			1 2 3	1 2 3	1 2 3	1 2 3
225 COMBINED RESOURCES			1 2 3	1 2 3	1 2 3	1 2 3

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			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
	INCOME (300)					
EARNED INCOME: 311 WAGES AND SALARIES			1 2 3	1 2 3	1 2 3	1 2 3
312 SELF-EMPLOYMENT			1 2 3	1 2 3	1 2 3	1 2 3
313 EARNED INCOME CREDIT			1 2 3	1 2 3	1 2 3	
314 OTHER EARNED INCOME			1 2 3	1 2 3	1 2 3	1 2 3
EARNED INCOME DISREGARDS/DEDUCTIONS: 321 EARNED INCOME DEDUCTIONS			1 2 3	1 2 3	1 2 3	1 2 3
322 WORK RELATED EXPENSES			1 2 3		1 2 3	1 2 3
323 CHILD OR DEPENDENT CARE			1 2 3	1 2 3	1 2 3	

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			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
UNEARNED INCOME: 331 RSDI BENEFITS			1 2 3	1 2 3	1 2 3	1 2 3
332 VETERANS BENEFITS			1 2 3	1 2 3	1 2 3	1 2 3
333 SSI			1 2 3	1 2 3	1 2 3	1 2 3
334 UNEMPLOYMENT COMPENSATION			1 2 3	1 2 3	1 2 3	1 2 3
335 WORKER'S COMPENSATION			1 2 3	1 2 3	1 2 3	1 2 3
336 OTHER GOVERNMENT BENEFITS			1 2 3	1 2 3	1 2 3	1 2 3

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
341 VALUE OF FOOD STAMPS/ HOUSING SUBSIDY			1 2 3		1 2 3	
342 CONTRIBUTIONS/ INCOME-IN-KIND			1 2 3	1 2 3	1 2 3	1 2 3
343 DEEMED INCOME			1 2 3	1 2 3	1 2 3	1 2 3
344 PA OR GA			1 2 3	1 2 3	1 2 3	1 2 3
345 EDUCATIONAL GRANTS/ SCHOLARSHIPS/LOANS			1 2 3	1 2 3	1 2 3	1 2 3
346 OTHER			1 2 3	1 2 3	1 2 3	1 2 3

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			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
350 SUPPORT PAYMENTS MADE TO CHILD SUPPORT AGENCY			1 2 3			
OTHER DISREGARDS/ DEDUCTIONS: 361 STANDARD DEDUCTION				1 2 3	1 2 3	1 2 3
362 UNEARNED INCOME DEDUCTION			1 2 3		1 2 3	1 2 3

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			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
363 SHELTER DEDUCTION				1 2 3		
364 STANDARD UTILITY ALLOWANCE				1 2 3		
365 MEDICAL DEDUCTIONS				1 2 3		

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			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
371 COMBINED GROSS INCOME			1 2 3	1 2 3	1 2 3	
372 COMBINED NET INCOME			1 2 3	1 2 3	1 2 3	
	NEED REQUIREMENTS (400)					
BASIC BUDGETARY ALLOWANCE: 411 SHELTER ONLY			1 2 3		1 2 3	1 2 3
412 OTHER BASIC BUDGETARY ALLOWANCE (SUBSISTENCE)			1 2 3		1 2 3	1 2 3
413 ALL BASIC BUDGETARY ALLOWANCES (COMBINED)			1 2 3		1 2 3	1 2 3
420 SPECIAL CIRCUMSTANCE ALLOWANCE			1 2 3		1 2 3	1 2 3

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Review No. ______________

ELEMENTS OF ELIGIBILITY AND PAYMENT DETERMINATION	QC ANALYSIS OF CASE RECORD *(Pertinent facts, sources of verification, reliability, gaps or deficiencies)*	FINDINGS OF FIELD INVESTIGATION *(Facts obtained, verification and substantiation, nature of errors)*	RESULTS			
			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OTHER (500)					
510 PROPER PERSON IN BUDGET			1 2 3		1 2 3	1 2 3
520 ARITHMETIC COMPUTATION			1 2 3	1 2 3	1 2 3	1 2 3
530 BENEFICIARY LIABILITY DETERMINATION					1 2 3	
540 GRANDFATHERED COVERAGE PROVISIONS					1 2 3	

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Form SSA-4340 (4-84)
Form HCFA-316(4-84)
Form FNS-380 (4-84)

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Work Sheet

ELEMENTS OF ELIGIBILITY AND PAYMENT DETERMINATION

Review No. ______________

ELEMENTS OF ELIGIBILITY AND PAYMENT DETERMINATION	QC ANALYSIS OF CASE RECORD *(Pertinent facts, sources of verification, reliability, gaps or deficiencies)*	FINDINGS OF FIELD INVESTIGATION *(Facts obtained, verification and substantiation, nature of errors)*	RESULTS			
			AFDC	FS	MQC	ADULT
(1)	(2)	(3)	(4)	(5)	(6)	(7)
550 OTHER STATE MEDICAID CRITERIA					1 2 3	
560 MONTHLY REPORTING			1 2 3	1 2 3	1 2 3	1 2 3

Form SSA-4340 (4-84)
Form HCFA-316 (4-84)
Form FNS-380 (4-84)

FOOD STAMP QUALITY CONTROL COMPUTATION SHEET

WORKSHEET START AT STEP 1 AND WORK THROUGH STEP 31. DO THE STEPS IN ORDER. BE SURE TO DROP ALL CENTS FROM ALL FIGURES EXCEPT INDIVIDUAL SHELTER COSTS. IF A NEGATIVE NUMBER RESULTS AFTER SUBTRACTING THE TWO NUMBERS, INSERT A ZERO.		ELIGIBILITY WORKER (1)	CORRECTED CERTIFICATION (2)	(3)	(4)	(5)
SELF-EMPLOYMENT INCOME (Include room and board payments) HOUSEHOLD MEMBER	SOURCE OF INCOME					
	1. Total gross self-employment income					
	2. Subtract monthly business costs					
	3. List monthly income before taxes					
WAGES, SALARIES OR OTHER INCOME FROM EMPLOYMENT (Do not count excluded income)						
	4. Add line 3 and all wage and salary income					
EDUCATIONAL GRANTS, SCHOLARSHIPS OR LOANS						
	5. Enter monthly income received from educational grants, etc.					
	6. Enter monthly tuition and mandatory fees					
	7. Subtract line 6 from 5					
	8. Add lines 4 and 7					
UNEARNED INCOME (Do not count excluded income)						
	9. Total unearned					
TOTAL GROSS INCOME						
	10. Add lines 8 and 9					
DEDUCTIONS						
	11. Multiply line 4 by 18% and enter result here					
	12. Subtract line 11 from 10					
	13. Enter standard deduction					
	14. Subtract line 13 from 12					
	15. Enter medical costs exceeding limit for households with members over 60					
	16. Subtract line 15 from line 14					
	17. Enter dependent care costs (Not to exceed limit)					
	18. Subtract line 17 from 16					
	19. If household includes members 60 or older or if any other household has shelter costs and its dependent care deduction (if any) is less than the limit, divide amount from line 18 by 2 and enter result here.					

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Form SSA-4340 (4-84)
Form HCFA-316 (4-84)
Form FNS-388 (4-84)

Review No. ____________

FOOD STAMP QUALITY CONTROL

COMPUTATION SHEET
(PAGE 2)

	ELIGIBILITY WORKER (1)	CORRECTED CERTIFICATION (2)	(3)	(4)	(5)
LIMIT ON SHELTER DEDUCTION Complete next 3 lines to find the maximum amount household can claim as a shelter deduction					
20. Enter maximum limit for combined shelter and dependent care deduction					
21. Enter dependent care deduction (same as line 17)					
22. Subtract line 21 from 20					
SHELTER COSTS Do not drop cents when listing cost of each shelter item. Drop the cents only after adding the cost of these items. Use either the utility standard or the actual cost for each utility bill.					
Rent or mortgage					
Tax and insurance					
Total utility standard					
Telephone (Basic rate)					
Electric					
Gas					
Oil					
Water and Sewerage					
Garbage and trash					
Installation of utilities					
Other					
23. Total shelter costs					
24. Enter amount from line 19					
25. Subtract line 24 from 23 (result equals excess shelter costs)					
NET MONTHLY INCOME					
26. Enter amount from line 18 (income after all deductions except shelter)					
27. If 60 or older enter line 25. For all other households enter amount from line 22 or 25 whichever is less (result equals shelter deduction)					
28. Subtract line 27 from 26 (result equals net monthly income)					
If amount from line 28 is less than income Eligibility Limit, go to line 29.					
ALLOTMENT LEVEL					
29. Enter Thrifty Food Plan for household's size					
30. Multiply line 28 by 30% and enter results here					
31. Subtract line 30 from 29. If result is less than $10 Enter $10 (Result equals monthly allotment)					

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Form SSA-4340 (4-84)
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Form Approved
OMB No. 0960-0313

INTEGRATED REVIEW SCHEDULE

(For Optional State Use)

PRIVACY ACT/PAPERWORK NOTICE ACT: This report is required under provisions of 45 CFR 205.40 (AFDC), 7 CFR 275.14 (Food Stamp), and 42 CFR 431.800 (Medicaid). This information is needed for the review of State performance in determining recipient eligibility. The information is used to determine State compliance, and failure to report may result in a finding of non-compliance.

I. REVIEW SUMMARY

1. Review Number
1a. Case Number
2. State and Local Agency Codes
3. Sample Month and Year
4. Stratum
5. Review Type

6. Disposition: AFDC/ADULT | FS | MA
7. Review Findings: AFDC/ADULT | FS
8. Amount of Error: AFDC/ADULT | FS

II. CASE INFORMATION

9. Most Recent Opening: ADULT
9a. Prior Assistance
10. Most Recent Action
11. Type of Action
12. No. of Case Members
13. Liquid Assets
14. Real Property (Excl. Home)
15. Countable Vehicle Assets
16. Other Non-Liquid Assets

REVIEW NUMBER	(For Optional State Use)

III. DETAILED PERSON - LEVEL INFORMATION

41. Person Number	42. Food Stamp Case A/N	43. AFDC/MA Case A/N	44. Relationship to Head of Household	45. Age	46. Sex	47. Race	48. Citizenship Status	49. Education Level	50. WIN and FS Work Reg.	51. Employment Status	52. Institutional Status

IV. TOTAL HOUSEHOLD INCOME, BY HOUSEHOLD MEMBER AND TYPE AND AMOUNT OF INCOME

53. Person Number	54. Type of Income	55. Amount of Income	56. Type of Income	57. Amount of Income	58. Type of Income	59. Amount of Income	60. Type of Income	61. Amount of Income

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REVIEW NUMBER | (For Optional State Use)

V. ELIGIBILITY REVIEW INFORMATION - MEDICAID

62. Eligibility Coverage Codes: Agency | OC

63. Initial Case Eligibility Status

64. Initial Case Liability Error

65. Amount of Excess Resources

VI. DETAILED ERROR FINDINGS

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66. Program Identification	67. Error Finding		68. Case Members with Errors (MA)	69. Element	70. Nature Code	71. Agency or Client	72. Dollar Amount	73. Discovery	74. Verification	75. Occurrence: Date	Time Period

76. Ineligible Persons with Federal Matching (AFDC Overpayment Case) — Counted | Not Counted

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REVIEW NUMBER	(For Optional State Use)

VII. PAYMENT REVIEW INFORMATION - MEDICAID

77. Dollar Amount of Paid Claims	78. Final Case Elig. Status	79. Revised Initial Case Liability Error	80. Spend-down Months	81. Total Claims Used to Offset Initial LU Errors	82. Final Dollar Amount of Case Liability Errors	83. Final Dollar Amount of Case Eligibility Errors

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VIII. OPTIONAL - FOR STATE SYSTEMS ONLY

1.
2.
3.
4.

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APPENDIX B

State Regressed Error Rates: Fiscal Year 1984

EXHIBIT 1.1
State Regressed Error Rates: Fiscal Year 1984

State	Case Error Rate (Percent of Cases in Error) Overpayments*	Case Error Rate (Percent of Cases in Error) Underpayments	Payment Error Rate (Percent of Dollars in Error) Overpayments*	Payment Error Rate (Percent of Dollars in Error) Underpayments
Connecticut	13.26	5.99	7.11	1.91
Maine	12.61	4.73	6.74	1.57
Massachusetts	17.90	5.20	9.86	1.90
New Hampshire	14.38	6.18	8.18	1.88
New York	16.88	8.70	10.14	3.23
Rhode Island	14.44	5.32	7.08	2.02
Vermont	17.92	5.92	9.71	1.51
Regional Total	16.55	7.72	9.67	2.83
Delaware	13.56	7.03	6.40	3.84
Dist. of Columbia	16.21	9.24	8.80	3.23
Maryland	14.02	5.98	6.85	1.33
New Jersey	15.62	7.51	7.47	2.16
Pennsylvania	19.85	7.56	10.41	2.03
Virginia	13.27	7.21	7.63	3.18
Virgin Islands	30.50	11.18	12.13	2.24
West Virginia	15.76	6.19	6.95	1.53
Regional Total	16.65	7.13	8.57	2.13
Alabama	18.18	6.76	13.35	2.98
Florida	15.70	8.60	9.00	2.48
Georgia	19.77	7.13	9.57	3.42
Kentucky	17.21	7.88	8.98	2.03
Mississippi	20.65	6.68	9.24	1.90
North Carolina	12.28	9.63	7.22	3.51
South Carolina	23.10	8.27	10.90	3.68
Tennessee	14.08	6.73	6.09	2.04
Regional Total	17.34	7.70	9.28	2.69
Illinois	19.64	7.34	8.31	2.92
Indiana	18.10	5.92	8.64	1.74
Michigan	13.75	6.25	6.46	1.54
Minnesota	16.74	5.98	9.77	2.10
Ohio	16.15	4.98	6.65	1.73
Wisconsin	15.12	7.89	9.60	3.20
Regional Total	16.22	6.14	7.55	2.11

*Includes overpayments to eligibles and payments to ineligibles

EXHIBIT 1.1 (continued)
State Regressed Error Rates: Fiscal Year 1984

State	Case Error Rate (Percent of Cases in Error) Overpayments*	Underpayments	Payment Error Rate (Percent of Dollars in Error) Overpayments*	Underpayments
Arkansas	17.23	5.95	9.66	2.23
Louisiana	17.17	7.66	10.16	1.71
New Mexico	19.83	7.95	11.83	2.23
Oklahoma	12.56	8.58	7.61	3.45
Texas	16.68	6.36	9.97	1.67
Regional Total	16.59	6.96	9.89	1.94
Colorado	17.35	6.95	10.66	2.03
Iowa	17.57	5.97	8.51	1.54
Kansas	14.19	5.50	7.35	2.31
Missouri	16.28	7.29	5.83	1.98
Montana	18.13	6.88	8.77	2.16
Nebraska	16.08	6.14	8.79	1.94
North Dakota	10.06	3.61	6.27	0.64
South Dakota	12.16	5.43	3.59	0.94
Utah	16.89	8.62	11.43	2.77
Wyoming	17.50	7.12	9.08	2.69
Regional Total	16.28	6.64	7.78	1.95
Alaska	16.36	11.77	9.29	1.89
Arizona	21.02	9.40	9.38	3.36
California	12.38	7.74	7.67	2.83
Guam	13.71	8.53	3.39	1.12
Hawaii	8.93	4.08	3.69	1.06
Idaho	15.40	5.83	6.88	1.81
Nevada	3.59	0.75	2.54	0.16
Oregon	13.99	5.12	9.18	2.05
Washington	16.09	6.72	9.23	2.59
Regional Total	13.52	7.21	7.83	2.53
U.S. Total	16.28	7.09	8.64	2.34

Source: Food Stamp Quality Control: Executive Overview FY 1984, USDA, Food and Nutrition Service, March 1986.

APPENDIX C

LIST OF EXPLANATORY VARIABLES

Appendix C
Explanatory Variables Examined for Inclusion in the Statistical Model

Dependent Variables*

STERROR	Dollar amount of State error finding.
ERROR	Natural logarithm of STERROR.
ERRFLAG	If case was found to have an error (equal to 1 if overpayment or ineligible).

Household Characteristics

CAF1	Total number of persons in Food Stamp case under review.
CAF2	Total number of persons who are in household but are members of a Food Stamp case not under review.
CAF3	Total number of persons in household who are not receiving food stamps.
OCCEMP	Total number of persons in household who are employed 30 hours or more or who are in military service.
OCCSELF	Total number of persons in household who are self-employed.
OCCNOEMP	Total number of persons in household who are not employed (e.g., incapacitated, full-time homemaker, student, or not actively seeking employment).
OCCUNEMP	Total number of persons in household who are unemployed (e.g., awaiting recall from layoff, on strike, out of work but actively seeking employment).
OCCBORN	Total number of persons in household who were born in the U.S.
OCCNAT	Total number of persons in household who are naturalized citizens.
OCCNOCIT	Total number of persons in household who are not U.S. citizens.
OCCLT3	Total number of persons in household aged 3 or under.
OCCLT6	Total number of persons in household under age 6.
OCCLT17	Total number of persons in household under age 17.

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*For each variable, we have also computed the mean and the difference of each individual case (from the mean). Differences from the mean are designated by a preceeding "X" (e.g., XCAF1).

OCC1859	Total number of persons in household aged 18-59.
OCC60	Total number of persons in household who are aged 60 or over.
ELDISS	Whether anyone in household is elderly <u>or</u> disabled (1=Yes).
DISABLED	Whether anyone in household is disabled (1=Yes).
HHAGE	Age of head of household.
HHSEX	Sex of head of household (1=Female).
HHCIT	Citizenship of head of household.
HHWHITE	Race of head of household (1=nonwhite).
NOTMEM	Whether there is a member of household who is <u>not</u> a member of the Food Stamp case under review (1=Yes).
NOTBORN	Whether there is a person in household not born in U.S. (1=Yes).
TWOAFDC	Whether State provides AFDC-U benefits <u>and</u> household receives AFDC <u>and</u> there is a spouse present in the household (Yes=1).

<u>Reported Income</u>

ALLOTMT	Total dollar amount of Food Stamp allotment.
FSMEM	Total dollar amount of Food Stamp allotment per person.
HHWAGE	Total dollar amount of household wages and salaries.
HHSELF	Total dollar amount of household self-employment income.
HHEITC	Total dollar amount of household earned income credit.
TOTEI	Total dollar amount of household earned income (HHWAGE + HHSELF + HHEITC + other earned income).
EIPCAP	Earned income per case member.
HHUNEARN	Total dollar amount of household unearned income.
TOTAFDC	Total dollar amount of AFDC grant.
OCCEI	Total number of persons with any form of earned income.
TOCCEI	Total occurences of earned income in household (counts multiple sources by an individual).
OCCAFDC	Presence of the reciept of AFDC.
OCCPAGA	Total number of persons with general assistance (GA) in household.

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OCCSSI	Total number of persons with SSI in household.
TOCCPA	Total occurences of public assistance income in household (includes AFDC, PA/GA, and SSI).
OCCPA	Total number of persons with public assistance income.
TOCCIUI	Total occurences of institutional unearned income (including RSDI, Veterans benefits, Unemployment Compensation, Workmen's Compensation, or Disability) in the household.
OCCIUI	Total number of persons in household with institutional unearned income.
TOCCOTH	Total occurences of other unearned income (includes deemed income, educational grants/scholarships, child support and other).
OCCOTH	Total number of persons in household with other unearned income.
HHAFDC	Whether head of household receives AFDC (1=Yes).
GROSS	Total dollar amount of household gross income.
NETINC	Total dollar amount of household net income (gross income less total deductions).
MEDICAL	Total dollar amount of medical deductions.
DCARE	Total dollar amount of dependent care deductions.
ERND	Total dollar amount of earned income deductions.
EXSHEL	Total dollar amount of excess shelter deductions.
TOTDED	Total dollar amount of all deductions (includes above plus standard).
MEDCOST	Total dollar amount of claimed medical costs.
SHLTCST	Total dollar amount of claimed shelter costs.
DEPCCST	Total dollar amount of claimed dependent care costs.
DEDCT	Count of the number of allowed deductions.
NONZERO	Total number of nonzero eligibility elements for the household.
LHHWAGE	Natural logarithm of HHWAGE.
LHHSELF	Natural logarithm of HHSELF

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LUNEARN	Natural logarithm of HHUNEARN
LTOTEI	Natural logarithm of TOTEI
LGROSS	Natural logarithm of GROSS
LNETINC	Natural logarithm of NETINC

"True" Income*

XE311	Presence of earned income (1=Yes).
XE321	Presence of earned income deduction (1=Yes).
XE323	Presence of dependent care deduction (1-Yes).
XE363	Presence of shelter deduction (1=Yes).
XE365	Presence of medical deduction (1=Yes).
XE364	Presence of standard utility allowance (1=Yes).
XE150A	Presence of ineligible household members (1=Yes).
XE331	Presence of RSDI benefits (1=Yes).
XE333	Presence of SSI benefits (1=Yes).
XE334	Presence of unemployment compensation (1=Yes).
XE336	Presence of other government benefits (1=Yes).
XE344	Presence of PA or GA benefits (1=Yes).
XE346	Presence of other unearned income (1=Yes).

Reported Resources

VEHICLE	Total dollar amount of vehicle assets.
TOTASS	Total dollar amount of all assets.
CAR	Whether vehicle assets are nonzero (1=Yes).
ANYASS	Whether household has any assets (1=Yes).
LVEHIC	Natural logarithm of VEHICLE.
LTOTASS	Natural logarithm of TOTASS.

*These variables incorporate information obtained by the QC reviewer.

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"True Resources*

XE210	Presence of liquid resources (1=Yes).
XE221	Presence of real property (1=Yes).
XE222	Presence of vehicles (1=Yes).
XE224	Presence of other non-liquid resources (1=Yes).

Other Measures

COMPLEX	An index of case complexity equal to the number of program eligibility elements (e.g., wage earnings, medical costs) that are present.
DIFDOLL	An index of the likelihood of error measured by weighting each program element that is present for the case by the dollar value of overpayments attributable to errors related to the particular element. Separate versions were computed for ineligibility error cases and overpayment error cases.
DIFCASE	Same as DIFDOLL but weighted by incidence of error.

Food Stamp Case Actions

EXPEDIT	Whether household received expedited service (1=Yes).
AUTHREP	Whether household used an authorized representative (1=Yes).
OCCREG	Total number of persons who are registered for work.
OCCEX	Total number of persons who are exempt from work registration.

State Indicator Variables

AL	ALABAMA
AK	ALASKA
AZ	ARIZONA
CA	CALIFORNIA
CO	COLORADO
CN	CONNECTICUT
DE	DELAWARE
DC	DIST OF COLUMBIA
FL	FLORIDA
GA	GEORGIA
HA	HAWAII

*These variables incorporate information obtained by the QC reviewer.

ID	IDAHO
IN	INDIANA
IA	IOWA
KS	KANSAS
KY	KENTUCKY
LA	LOUISIANA
ME	MAINE
MD	MARYLAND
MA	MASSACHUSETTS
MI	MICHIGAN
MN	MINNESOTA
MS	MISSISSIPPI
MO	MISSOURI
MT	MONTANA
NB	NEBRASKA
NV	NEVADA
NH	NEW HAMPSHIRE
NJ	NEW JERSEY
NM	NEW MEXICO
NY	NEW YORK
NC	NORTH CAROLINA
ND	NORTH DAKOTA
OH	OHIO
OK	OKLAHOMA
OR	OREGON
PA	PENNSYLVANIA
RI	RHODE ISLAND
SC	SOUTH CAROLINA
SD	SOUTH DAKOTA
TN	TENNESSEE
TX	TEXAS
UT	UTAH
VT	VERMONT
VA	VIRGINIA
WA	WASHINGTON
WV	WEST VIRGINIA
WI	WISCONSIN
WI	WYOMING
GM	GUAM
VI	VIRGIN ISLANDS

Socioeconomic Measures of Geographic Area in which Household Resides

POP	Total population.
BIGCITY	Household resides within one of 30 largest cities (1=Yes).
VACANT	Percent of housing units that are vacant.
BLACK	Percent of population that is Black.
SPANISH	Percent of population that is Spanish.

FAMHH	Percent of households that are families.
FEMHH	Percent of households that are female headed.
ED12	Percent of persons 25 years of age or older with 12 or more years of education.
UNEMP	Percent of civilian labor force that is unemployed.
ARGI	Percent of civilian labor force employed in agriculture.
MANU	Percent of civilian labor force employed in manufacturing.
MEDINC	Median family income.
POVERTY	Percent of persons with incomes below the 1979 OMB poverty line.
MEDRENT	Median gross rent for renter-occupied housing units.
POPDENS	Total persons per square mile.
BIRTH	Births per 1,000 resident population.
CRIMET	Number of crimes per 100,000 resident population.
CRIMEV	Number of violent crimes per 100,000 resident population.
POVDENS	Poverty density, equal to (POVERTY) x (POPDENS).