Using Two-Sample Methods to Correct for Reporting Bias in Surveys*

Bruce D. Meyer
University of Chicago and NBER

and

James X. Sullivan
University of Notre Dame

December 2008

Abstract

Benefit receipt in major household surveys is often underreported. This understatement has major implications for our understanding of the economic circumstances of disadvantaged populations, program takeup, the distributional effects of government programs, and studies of other program effects. We provide a new econometric method for estimating the determinants of reporting that uses two data sources with overlapping demographic characteristics rather than requiring matched individual data. This method compares the characteristics of those who report receipt in the survey to the characteristics of recipients in the administrative data to determine the influence of those characteristics on reporting. Our estimates using this two sample estimation procedure indicate that observable characteristics are related to underreporting in the case of the Food Stamp Program (FSP). We then show the how these results can be used to correct for underreporting bias in studies of FSP participation or the distributional effects of the FSP. Our results also have implications for studies that use FSP receipt as an explanatory variable.

* This research received support from the USDA Food Assistance Research Development Grant Program. We thank Lisa Barrow, Bob Dalrymple, Luojia Hu, Dan Hungerman, Robert LaLonde, and attendees at two USDA Research Development Grant Workshops, and the GSB Micro Lunch for helpful comments. We also thank April Wu for excellent research assistance. Meyer: Harris School of Public Policy Studies, University of Chicago, 1155 E. 60th Street, Chicago, IL 60637, bdmeyer@uchicago.edu. Sullivan: University of Notre Dame, Department of Economics and Econometrics, 447 Flanner Hall, Notre Dame, IN 46556, sullivan.197@nd.edu.

I. Introduction

Comparisons of receipt of food stamps in surveys to administrative numbers indicate that food stamp receipt is underreported substantially. For example, more than forty percent of months of food stamp receipt were not reported in the Current Population Survey (CPS) in 2004. This underreporting is evident in several large national surveys, and in some of these surveys the extent of underreporting has grown over time. An important consequence of underreporting is that it may lead to significant bias in studies that examine the determinants of participation in the Food Stamp Program (FSP), the distributional consequences of this program, and other program effects.

This paper provides a new method of addressing underreporting bias in studies of that rely on survey reports of program receipt. We present a new econometric method of estimating the determinants of reporting that uses two data sources with information on the same demographic characteristics, but from different people rather than matched individuals. This method compares the characteristics of those who report receipt in a survey to the characteristics of recipients in administrative data to determine the influence of those characteristics on reporting. To implement this procedure for the FSP, we use administrative microdata from the Food Stamp Program Quality Control (FSPQC) Database and survey data from the CPS. Our estimates using this two sample estimation procedure indicate that observable characteristics are significantly related to underreporting.

An important consequence of underreporting is that it may lead to significant bias in studies that rely on survey reports of program receipt. For example, a number of studies have examined the likelihood that those eligible for food stamps actually participate in the program. These studies show that participation rates among eligibles are well below one. However, given the extent of underreporting, a major part of what appears to be non-participation may actually be recipients whose receipt is not recorded in the household survey. We demonstrate how to use our multivariate two sample estimates to correct for underreporting bias in studies of FSP participation. Underreporting will also bias studies of the distributional consequences of the FSP. For example, studies that examine the extent to which food stamps increase the resources of poor families will understate the impact of the FSP due to underreporting of food stamps. We show how to correct for underreporting bias in such studies using estimates from our two sample procedure. Our results also suggest biases in regressions with food stamp receipt as an explanatory variable. Furthermore, instrumental variable methods will not eliminate these biases given the correlation we find between the measurement errors and common explanatory variables.

A better understanding of underreporting and how it may bias various studies of food stamps has important implications for both policy makers and researchers. Policy makers have long been concerned with low participation rates in the FSP, and have recently taken steps to increase participation (GAO 2004). In addition, a more accurate estimate of program take up should provide better information about who is benefiting from the FSP, why families choose not to participate in the program, or how individual characteristics affect participation. Such information could be used to increase take up and better target the program. In addition, correcting for underreporting bias will yield better measures of the well-being of the worse off, and provide a clearer picture of the distributional consequences of the FSP. Lastly, the methods presented in this paper could be used to analyze underreporting for other transfer programs that collect administrative microdata. A better understanding of underreporting of transfers, and how it varies across demographic groups, would also allow us to improve our household surveys.

In the following section, we summarize findings on the extent of food stamp underreporting in large surveys. In Section III, we discuss how underreporting leads to bias in studies of the FSP. We describe the survey and administrative microdata used in our analyses in Section IV, and explain the two sample estimation procedure in Section V. We present the estimates from this procedure in Section VI, and discuss how to use these estimates to address underreporting bias in Section VII. Conclusions are offered in Section VIII.

II. Under-reporting of Program Receipt in Surveys

A number of studies have documented significant underreporting of food stamps in large national surveys such as the CPS or the Survey of Income and Program Participation (SIPP).[1] Several studies estimate underreporting by using administrative microdata that is directly linked to survey data. In perhaps the most comprehensive of these matching studies, Marquis and Moore (1990) shows that 23 percent of survey respondents who were food stamps recipients according to administrative microdata failed to report participation in the 1984 SIPP. Also using the 1984 SIPP, Bollinger and David (1997) find a nonreporting rate of 12 percent. They aggregate survey responses to the household level, ignoring nonreporting that results from confusion about who in the

[1] Underreporting is not unique to food stamps. In fact, there is evidence of significant underreporting in many government transfer programs (Meyer, Mok, and Sullivan 2008). Excellent summaries of data reporting issues in surveys include Moore, Stinson and Welniak (2000), Bound, Brown and Mathiowetz (2001), and Hotz and Scholz (2002).

household are the actual recipients. Bollinger and David also conclude that female recipients are less likely to fail to report receipt. Taeuber et al. (2004), which examines FSP administrative records in Maryland linked to the national 2001 Supplementary Survey (American Community Survey), find a nonreporting rate of 38 percent (47 percent calculated a second way).

The main limitation to direct matching of survey and administrative microdata at the individual or household level is that such matches are rarely available, and when these matched data are available, it is typically only for a short time period and for a small subset of the survey respondents, such as a single state. An alternative approach is to compare reported receipt in the survey weighted up to the population to administrative reports of the actual number of recipients or actual dollars distributed. Studies that use this approach also find evidence of substantial underreporting. For example, Primus et al. (1999), which compares weighted dollars of reported food stamps for households in the CPS Annual Demographic File (ADF) to administrative numbers, finds that the underreporting rate increased from 23.8 percent in 1990 to 37.3 percent in 1997. Bitler, Currie, and Scholz (2003) estimate underreporting rates between 1995 and 1999 of about 14 percent in the CPS Food Security Supplement and about 11 percent in the SIPP. Cody and Tuttle (2002) calculate underreporting rates for the CPS ADF that range from about 21 percent in 1991 to 36 percent in 1999.

Meyer, Mok, and Sullivan (2008) document the degree of underreporting of food stamps in several major household surveys and for many years by comparing the weighted total of reported food stamps receipt by households in surveys with totals made available by the US Department of Agriculture, Food and Nutrition Services. Results for the CPS, SIPP, the Panel Study of Income Dynamics (PSID), and the Consumer Expenditure (CE) Survey are reported in Figure 1 (for dollars) and Figure 2 (for months). The dollar and month reporting rates are remarkably similar, suggesting that almost all of the underreporting is due to understating the number of months of receipt. There is other evidence that finds that monthly amounts are actually quite close to the true average for several programs and datasets. Previous research indicates that about two-thirds of the underreporting of food stamps months in surveys results from failure to report receipt at all (Moore, Marquis and Bogen, 1996). The reporting rates in Figures 1 and 2 show that food stamps are significantly under-reported in each of these surveys. Moreover, reporting rates have fallen over time. As shown in Figure 2, between 1973 and 2002, reporting rates for food stamp months fell in the PSID from 0.884 to 0.625. Between 1987 and 2004, reporting rates in the CPS fell from 0.739 to 0.566. The SIPP typically has the highest reporting rate for the FSP program, and these have fluctuated but not steadily declined over time.

III. Underreporting Bias in Studies of the Food Stamp Program

The underreporting of food stamps in large surveys discussed above can lead to significant bias in studies of the Food Stamp Program. For example, a number of studies have examined participation rates for the FSP among eligibles or potential eligibles.[2]

[2] For example, using data from the SIPP, Blank and Ruggles (1996) estimate take up rates among single mothers that are close to 50 percent in 1986-1987. Zedlewski and Brauner (1999) use data from the National Survey of American Families to show that many welfare leavers do not participate in the FSP despite remaining eligible. Fraker and Moffitt (1988) find that 38 percent of eligibles participate using the 1979 Panel of the Income Survey Development Program (ISDP), the experimental precursor to the SIPP. Using data from the Health and Retirement Survey, Haider, Jacknowitz, and Schoeni (2003) find that only

Underreporting of food stamps will bias such estimates because much of what appears to be non-participation may actually be recipients whose receipt is not recorded in the household survey.[3] To demonstrate the potential importance of underreporting bias we can adjust estimates of participation from the literature for underreporting using the comparison-to-aggregate results in Figure 1. For example, adjusting for underreporting bias in the SIPP would increase take up estimates in Blank and Ruggles (1996) by 15 percent from 0.52 to 0.60.[4] An important limitation with this adjustment is that it assumes that the underreporting rate does not vary across different demographic groups. We show how to relax this assumption in Section VII.

Other studies of the FSP use survey data to examine the distributional consequences of the program. These studies show that the FSP has very important distributional consequences at the bottom. For example, new, alternative measures of poverty reported by U.S. Census (2006) indicate that Food Stamps and other noncash transfer programs lift a large number of people out of poverty. Several studies show that the FSP increases the resources of those in poverty and plays an important role in filling the poverty gap (Ziliak 2004; Bishop, Formby, and Zeager 1996). Meyer and Sullivan (2006) show that the FSP has an important effect on estimates of changes in family income over time. By not accounting for underreporting of food stamps, these studies understate the distributional effects of the FSP.[5, 6]

---

about a third of the elderly who are eligible participate in the FSP. For a survey of the literature on take-up and other transfer programs see Currie (2004).

[3] Survey underreporting of Food Stamps is not an issue in other studies of take up that use administrative microdata on Food Stamps to identify participation (GAO 2004; USDA 2003, 2005).

[4] The estimate from Blank and Ruggles is from Table 1, Panel B, which includes left-censored and nonleft-censored spells of eligibility and participation. Our adjustment is based on the reporting rate for months in the SIPP for 1986-1987 (0.87).

[5] Other studies do address underreporting bias in the distributional analyses of the FSP. For example, see Primus et al. (1999) or Jolliffe et al. (2005).

To demonstrate the potential underreporting bias in studies of the distributional consequences of the FSP, we use data from the 2002 CPS ADF (for calendar year 2001) to calculate alternative poverty rates that include food stamps following the procedure of several studies of alternative poverty (for example see U.S. Census 2006). We then adjust these alternative poverty estimates for underreporting by scaling up the dollars of food stamps in the CPS sample using the reporting rates for food stamps from Figure 1.[7] As shown in Figure 3, including food stamps in the measure of resources used to determine poverty reduces poverty substantially. The official poverty rate in 2001 was 11.7 percent. Adding reported food stamps reduces the poverty rate to 11.3 percent, which is a decrease in the number of poor individuals of 1.1 million. After adjusting for underreporting of food stamps in the CPS, the poverty rate falls even further, to just under 11 percent, effectively lifting another 900,000 individuals out of poverty. The differences are particularly large when looking at extreme poverty, such as those below 25 percent of the official poverty line. Including reported food stamps reduces those below 25 percent of the poverty threshold by 14 percent. After adjusting for underreporting, this measure of extreme poverty falls by an additional 14 percent. These results in Figure 3 demonstrate that underreporting bias will lead to a significant understatement of the distributional effects of the FSP. However, these simple adjustments assume that underreporting is random—that the characteristics of FSP households that do not report receipt in surveys are the same as those of FSP households

---

[6] Other studies of the distributional consequences of the FSP that may be affected by underreporting bias include those that look at the consumption-smoothing role of the FSP (Ziliak and Gundersen, 2003; Blundell and Pistaferri, 2003).

[7] We allocate a benefit amount to CPS households that do not report receipt based on the amount each household would be eligible for if they did receive. We allocate these benefits to the nonreceivers with the highest predicted probability of receipt following the procedure in Meyer and Sullivan (2006).

that do report receipt. Below we demonstrate how to address underreporting bias in distributional analyses, allowing underreporting to vary with observable characteristics.

IV. Two Sample Estimation Procedure

Taking advantage of administrative microdata, we estimate underreporting rates that vary by individual characteristics. Our approach does not require the administrative and survey microdata to be matched. Unlike matched data, which is typically available for one dataset, one program, in one state and year, our method could be applied to the entire country. and be used to adjust current as well as past data on program receipt. Suppose we are interested in estimating how the likelihood of reporting program receipt in a survey dataset, conditional on truly receiving benefits from the program, varies with a set of characteristics X. This information would allow us to determine how participation or take-up estimates are biased by underreporting. Suppose we have a sample of program recipients from an administrative micro dataset that itself is a sample from the universe of all recipients, or in fact include all recipients. Suppose that we also have a sample of respondents to a representative household survey, but not all true recipients report that they are recipients in the survey. The distribution of individual characteristics in the administrative data, weighted by the probability of reporting, should be the same as the distribution of individual characteristics in the survey data of reporting recipients.

Formally, let $y_i = 1$ if person i with characteristics X_i reports receipt in the survey dataset conditional on receiving benefits. Let S be the set of observations i from the survey dataset that is a sample from the subset of true recipients who report receipt. Let A be the set of observations from the administrative sample that is drawn from all recipients. Further assume that $F(X_i\beta)$ is the probability that person i with characteristics X_i reports receipt in the survey dataset conditional on receiving benefits. Consider the moment equation:

$$\sum_{i \in S} X_i = k \sum_{i \in A} X_i F(X_i \beta)$$

where k accounts for the possibly differing sampling rates in the two datasets. This equation just says that the mean of x should be the same in the two datasets once one adjusts the administrative data for the likelihood of being included in the survey data. Given that in practice the samples are likely to have nontrivial weights, the moment condition needs to be modified to be

$$\sum_{i \in S} w_i X_i = \sum_{i \in A} w_i X_i F(X_i \beta),$$

where the w_i are sample weights. To use this moment condition to estimate the determinants of reporting, one simply finds the $\hat{\beta}$ that solves equation (x).

Guell and Hu (2006) applied this approach to a slightly different problem (but one that is formally very similar). Guell and Hu examine the duration of unemployment spells using repeated cross-section data. They estimate the individual level determinants of the unemployment exit rate by comparing the size and characteristics of unemployment cohorts of various durations in successive time periods. Following this general logic, if one has a random sample of recipients from an administrative dataset and a random sample of reporting recipients from a survey dataset, one can estimate the determinants of reporting. Intuitively, one can compare the characteristics of those who report to the characteristics of the full set of recipients, and thus determine the influence of those characteristics on reporting.

As do Guell and Hu, we assume that F has a logit form, allowing us to integrate this moment condition to obtain a pseudo-likelihood function

$$f(b) = \sum_{i \in S} w_i X_i b + \sum_{i \in A} w_i \log(1 - \Lambda(X_i b)) . \tag{4}$$

This function can be easily maximized using standard methods since it is globally concave. Let n_A be the number of observations in the administrative data and let n_S be the number of observations in the survey dataset. For purposes of asymptotics assume n_S is a function of n_A, i.e. $n_S = n_S(n_A)$, and $\alpha = \lim_{n_A \to \infty} n_S / n_A$.

Using standard arguments (Amemiya, 1985), one can show that

$$\sqrt{n_A}(\hat{\beta} - \beta) = \left[\frac{1}{n_A} \sum_{i \in A} w_i \Lambda(X_i \beta^*)(1 - \Lambda(X_i \beta^*) X_i X_i' \right]^{-1} \left[\sqrt{\frac{n_S}{n_A}} \frac{1}{\sqrt{n_S}} \sum_{i \in S} w_i X_i - \frac{1}{\sqrt{n_A}} \sum_{i \in A} w_i X_i \Lambda(X_i \beta) \right]$$

where we are applying the multivariate mean value theorem row by row to the matrix in the first term in brackets, as each row of this matrix is evaluated at a different point (β^*) between β and $\hat{\beta}$. One can then show that

$$\sqrt{n_A}(\hat{\beta} - \beta) \to \mathrm{N}(0, C^{-1} B C^{-1})$$

where

$$C = E[w_i \Lambda(X_i \beta)(1 - \Lambda(X_i \beta) X_i X_i' \mid i \in A]$$
$$B = \alpha Var[w_i X_i \mid i \in S] + Var[w_i X_i \Lambda(X_i \beta) \mid i \in A].$$

The asymptotic variance is then $n_A^{-1} C^{-1} B C^{-1}$ which can be estimated by inserting $\hat{\beta}$ in the sample analogs of C and B.

The key assumption for consistency of this approach is that the survey dataset is a sample from a non-random subset of the same population from which the administrative data is sampled. In practice, this assumption requires that the same time period must be used for both the survey and the administrative data and that one must assume that nonrecipients do not report receipt in the survey. This latter assumption given that some research using matched microdata indicates that misreporting rates for FSP participation among nonrecipients are small (Bollinger and David, 2001). Other research find small, but nontrivial misreporting among non-recipients (Meyer, Mok and Sullivan 2008), so this possibility needs to be seriously considered. We intend to investigate the robustness of results to deviations from this assumption. Some results are provided in Appendix 2.

V. Data

In the analyses that follow, we use both administrative and survey microdata. Administrative microdata for the FSP are available in the FSPQC Database. This database contains detailed demographic, economic, and FSP eligibility information for a large, nationally representative sample of FSP units. The FSPQC data are provided by Mathematica Policy Research, Inc. for the USDA, Food and Nutrition Service, and public use files are available online for each fiscal year from 1996 through 2004. For our analyses we will use data from the 2001 and 2002 fiscal years. For more information on the FSPQC, see USDA (various years).

The survey microdata for the analyses that follow come from the CPS ADF for 2002.[8] This survey includes questions regarding whether or not households receive food

[8] Prior to 2002, the ADF was referred to as the March Supplement. Starting in 2003, the ADF was renamed the Annual Social and Economic Supplement (ASEC).

stamps, the dollar amount of receipt, and months of receipt for the calendar year prior to the interview. We focus on the CPS because this survey is often used by researchers to examine participation in the FSP, and to determine the distributional consequences of the FSP. However, the analyses we present below could be applied to other surveys that provide information on food stamp receipt including the SIPP, the PSID, and the CE Survey.

In order to implement our two sample estimation procedure, we need to address a number of definitional differences across these data sources. For example, because the CPS sample does not include Guam and the Virgin Islands, we exclude observations from these territories in the FSPQC data.[9] Also, food stamp receipt in the CPS refers to the previous calendar year, while the FSPQC is a sample of the monthly caseload for each month of a fiscal year (FY). We use data from both sources that reflect receipt in a typical month during calendar year 2001. Thus, for the CPS, we use data from the 2002 ADF, and multiply the household weights by the reported number of months receiving food stamps and divide by 12. From the FSPQC data we use monthly household observations from January through September of 2001 from the FY 2001 data and from October through December of 2001 from the FY 2002 data. For the FSPQC data we use the annual weight divided by 12. To reduce the prevalence of reported receipt by non-recipients, we exclude all CPS observations where FSP receipt is imputed and proportionally reweight the non-imputed recipients so they have the same total weight. Results for the sample including imputed values are reported in the Appendix tables.

[9] A small number of food stamp recipients in the CPS may not be in the universe from which the FSPQC data is drawn because the universe excludes those that receive food stamps in error or those that qualify only under disaster-related rules.

To compare observable characteristics across our two data sources, we use the characteristics of a designated head of the household.[10] Because the unit head is not necessarily defined the same way in the FSPQC data and the CPS, we select a unit head using a method that is comparable across the two data sources.[11] In the FSPQC data, we specify the head of the household as the person designated as the head of the household in the FSPQC data, unless the FSPQC designated head is male and a female spouse is present. In this latter case, we designate the spouse as the head. In the CPS, we designate as the head, the person that is most likely to be the head of the food stamp unit, always designating the female in the case of a married couple household (see Data Appendix for more details). While this approach does not ensure that we define a household head consistently across the two data sources in all cases, this definition is consistent for the vast majority of food stamp households.[12]

In the analyses that follow, we compare characteristics that are defined similarly in the data sources. These characteristics include the regional indicators and characteristics of the head such as age, race, gender, educational attainment, and

---

[10] The unit of observation in the FSPQC data is a household. Each household includes at least one food stamp unit (FSU), but not all members of the household are necessarily members of the food stamp unit. Although some food stamp households (about 2 percent) contain multiple FSUs, only one FSU from each food stamp household is included in the FSPQC data. In the CPS, food stamps are reported at the household level.

[11] In the CPS, the head or "householder" is defined as "the person (or one of the persons) in whose name the housing unit is owned or rented (maintained) or, if there is no such person, any adult member, excluding roomers, boarders, or paid employees" (U.S. Census (2002)). In the FSPQC, the head of the household is not clearly defined. Officials at the USDA have told us that, in practice, the QC reviewer typically designates as the head of the household whoever is designated as the head on the food stamps certification file. For food stamp units that include children and parents, this is almost always one of the parents.

[12] For example, in a multigenerational CPS household with children, it is not clear whether the grandmother or the mother should be designated as the head of the household in order to match the definition of the head in the FSPQC data. Based on the household composition of reported FSP participants in the CPS, ambiguous cases such as these account for less than 5 percent of all households.

citizenship status.[13] Means for these characteristics are presented in Table 1. While the differences in mean characteristics are small, some of these differences are statistically significant suggesting that underreporting does vary with observable characteristics. For example, the fact that the fraction without a high school degree in the FSPQC data is greater than that in the CPS suggests that those without a high school degree are less likely to report. There is also evidence that males and minorities are less likely to report.

VI. Two Sample Estimation Results

Before considering the multivariate two-sample results on the determinants of reporting, it is worth considering the one explanatory variable case. We report these estimates in column 1 of Table 2. We report estimates of β, as well as standard errors and the marginal effects of the covariates.[14] When the model is estimated with only a constant, the point estimate is 0.552, which implies that the unconditional reporting rate for food stamps in the 2001 CPS, $\Lambda(\hat{\beta})$, is equal to 0.635. This matches the reporting rate for the CPS in 2001 in Figure 2. The remaining univariate estimates in column 1 provide some evidence that reporting of food stamps is related to observable characteristics. As in Table 1, we again see that those without a high school degree and males are less likely to report receipt.

In the case of one binary explanatory variable, the logit model is perfectly general and model just reproduces a result we analytically derive here. Consider a variable x that

[13] Other characteristics that are available in both data sources, such as household composition, employment status of the head, or measures of household income, are not included in our analyses because it is difficult to construct measures of these characteristics that are defined comparably in the FSPQC data and the CPS.
[14] For continuous variables we report average derivatives. For binary variables we report the average discrete difference when the variable is changed from zero to one.

takes on two values, 0 and 1. Let R be the overall probability of a recipient reporting receipt, and R_0 be the probability when x=0, and R_1 be the probability when x=1. Let $\bar{x}_A$ be the mean of x in the administrative dataset and $\bar{x}_S$ be the mean of x in the survey dataset. Using the laws of probability and some algebra we can derive (see Appendix 3) that

$$(R_1 - R_0) = R\frac{(\bar{x}_S - \bar{x}_A)}{\bar{x}_A(1-\bar{x}_A)}.$$

This equation says that if we consider a binary variable such as male, the difference in the reporting rates between men and women is just the difference in the mean share that is male in the two datasets $(\bar{x}_S - \bar{x}_A)$ times the reporting rate R, times the inverse of the product of the share male and one minus that share $\bar{x}_A(1-\bar{x}_A)$. This last expression is bounded above by ¼, so $\frac{R}{\bar{x}_A(1-\bar{x}_A)} > 4R$. Thus, the difference in reporting rates is likely to be much bigger than the difference in means between the two datasets. We can see this by comparing column 1 and the difference in means in column 6. The difference in reporting will also always have the same sign as the difference in means because R>0.

The main advantage of the two sample estimation procedure is that it allows us to examine the relationship between observable characteristics and the likelihood of reporting in a multivariate framework. The estimates in columns 2 through 5 show results that differ from the univariate specifications. In each of these specifications, the p-values reported near the bottom show that we can strongly reject that observable characteristics are not related to reporting. In all specifications age is positively related to the likelihood of reporting, but the marginal effect is small. The estimates also suggest that males are about 6.6 percentage points less likely to report than females.[15] The estimates in Table 2 also indicate that those in the South and Northeast are more likely to report that those in the Midwest. In the specification in column 5, the estimate for race indicates that whites are 5.2 percentage points more likely to report than nonwhites.

VII. Using Two Sample Estimates to Address Underreporting Bias

Another key advantage of estimating underreporting in our multivariate framework is that these estimates can easily be used to correct for underreporting bias in studies of program participation. We demonstrate how to adjust bias in studies of take up or participation in the FSP and studies of the distributional consequences of the FSP.

A. Correcting Estimates of Food Stamp Program Participation

The estimates of FSP underreporting that vary by individual characteristics that we presented in Table 2 can be used to adjust estimates of the relationship between characteristics and program participation. Suppose we estimate how reported receipt conditional on eligibility varies with characteristics X. This type of estimation is what most participation studies do, though we are emphasizing here that what is called participation is really the intersection the event participation and reporting receipt. To obtain the determinants of true participation we use the simple result from probability that $P(A) = P(A \cap B) / P(B \mid A)$. Here, A is the event participation in the FSP, and B is the event report receipt in the household survey. Suppose a conventional participation

[15] Studies using direct matches of administrative and survey microdata have also concluded that males are less likely to report receipt of food stamps (Bollinger and David 1997).

equation is estimated using a logit model. Thus, it is assumed that P (A $\cap$ B) conditional on X_i is $\Lambda(X_i\gamma)$. Then if P (B | A) conditional on X_i is $\Lambda(X_i\beta)$ as above, then our desired object P(A) conditional on X_i, the true participation rate, which we call $R(X_i)$, is just $\Lambda(X_i\gamma)/\Lambda(X_i\beta)$.

Derivatives of $R(X_i)$ differ from derivatives of $\Lambda(X_i\gamma)$. In fact, they take the form

$$\frac{\partial R_i}{\partial X_i} = \frac{\Lambda(X_i\gamma)(1-\Lambda(X_i\gamma))\gamma - \Lambda(X_i\gamma)(1-\Lambda(X_i\beta))\beta}{\Lambda(X_i\beta)}. \tag{5}$$

Whereas the derivative of the assumed participation rate for observation i is just $\Lambda(X_i\gamma)(1-\Lambda(X_i\gamma))\gamma$.

To implement this procedure, we present estimates from a simple participation equation using data from the 2002 CPS. We estimate a logit model of the relationship between observable characteristics and food stamp participation among potential eligibles using a sample of all CPS households with income below 130 percent of the poverty line.[16] Estimates from this simple participation model are presented in Columns 1 and 3 of Table 3.[17] These estimates show that among potential eligibles, minorities, those without a high school degree, and females are more likely to participate in food stamps than other household heads. However, these estimates of the relationship between observable characteristics and food stamp participation are biased because they do not account for underreporting. Using the estimates from Table 2, we compute average

[16] The gross income test requires food stamp recipients to have household monthly income below 130 percent of the poverty line. Other eligibility requirements include a net income test and an asset test. These specifications examine the probability of participation among a sample of potential eligibles, rather than the probability of take up among eligibles. The latter cannot be estimated using CPS data because the data are not sufficient to identify eligible households.

[17] For the estimates in Table 3, we replicate the sample of households with income under 130 percent of the poverty line 12 times to construct household-month observations using information on the number of months of reported FSP receipt in the previous year. Standard errors are adjusted to account for multiple observations from the same household.

derivatives that adjust for underreporting by calculating the weighted average of Equation 5. These adjusted estimates (columns 2 and 4) differ from the unadjusted estimates. For example, because those without a high school degree are less likely to report receipt (as shown in Table 2) estimates of the effect of being a high school dropout on participation are biased downward. The adjusted average derivative (0.114) is nearly 30 percent larger than the unadjusted average derivative (0.088). Our adjusted estimates also indicate that unadjusted estimates for the effect of age, race, and gender on participation are biased toward zero due to underreporting.

B. A Second Participation Correction Method

There is also a second way to calculate underreporting corrected estimates of program participation. One can calculate the likelihood that a person participates by comparing the characteristics of the group of potential participants to the characteristics of the recipient population. A natural way to do this is to reverse the role of the administrative and survey datasets in our two-sample estimation methods. Specifically, one now simply finds the $\hat{\delta}$ that solves the moment condition,

$$\sum_{i \in S} w_i X_i = \sum_{i \in A} w_i X_i \Lambda(X_i \delta),$$

where participation among the population of potential participants is of the logit form $\Lambda(X_i\delta)$ and now A is the sample of all potential program participants from the survey data and S is a sample from the administrative data that is from the subset of potential participants that actually receives benefits.

Estimates using this approach are reported in Table 4 for our FSP example. The estimates of participation corrected for mis-reporting have some similarities and some differences vis a vis those in Table 3. Many of the estimates are different in magnitude than those in Table 3, though we have not performed a test of the statistical significance of the differences yet. However, seven of the eight derivatives are moved by the Table 3 correction in the direction of the Table 4 estimates. In addition, all eight are of the same sign. It would be helpful to have an interpretation of the difference between these two approaches. A very preliminary effort in this direction can be found in Appendix 3.
In an important sense, this approach is just the multivariate equivalent of the preferred approach taken by the USDA in calculating takeup rates. Their approach uses administrative numerators and survey based denominators.

C. Distributional Analyses

Similar to the procedure above, the estimates in Table 2 can be used to impute receipt among those not reporting receipt. Such imputations are helpful to account for underreporting in distributional analyses. In a survey, once we have computed the eligible population, a sensible imputation strategy might be to allocate unreported receipt to the eligibles who do not report receipt in proportion to the likelihood that they are receiving non-reporters. This probability is just the take-up rate times one minus the reporting rate or $(1-\Lambda(X_i\beta))\ \Lambda(X_i\gamma)/\Lambda(X_i\beta)$. Another approach might be to allocate benefits first to those with the highest values of this probability.

VIII. Discussion and Conclusions

Program receipt is significantly underreported for most programs in the main large, nationally representative surveys. For example, comparisons to administrative aggregates indicate that months of food stamp receipt in the CPS is underreported by 30 to 43 percent in recent years. We show that this underreporting leads to significant bias in studies of food stamps participation or the distributional consequences of the FSP.

Simple adjustments for underreporting do not account for differences in the likelihood of reporting across demographic groups. In this paper we illustrate how to estimate the relationship between observable characteristics and the likelihood of reporting in a multivariate framework. This method compares the characteristics of those who report receipt in the survey to the characteristics of recipients in the administrative data to determine the influence of those characteristics on reporting. Estimates from our two sample multivariate procedure indicate that observable characteristics are related to underreporting.

We also show how our two sample estimation procedure can be used to correct for underreporting bias in studies of program participation. Comparisons of unadjusted and adjusted estimates of the relationship between observable characteristics and program participation indicate that underreporting bias can be substantial. In addition, we demonstrate how one could use our procedure to adjust for underreporting bias in studies of the distributional consequences of the FSP.

Applications of our two sample estimation approach extend beyond studies related to food stamps. For example, a similar approach could be used to estimate the relationship between underreporting and observable characteristics in the AFDC/TANF program. More generally, our estimation approach can be applied whenever administrative microdata that include demographic information are available for a random sample of program recipients. This approach is more broadly applicable than direct matches of administrative microdata and survey microdata, because our approach could easily be implemented for many surveys and for many years. Finally, this study suggests a further use of administrative microdata for random samples of program participants, and the advantages of collecting variables in those data that are defined in the same way in administrative and survey data.

References

Amemiya, Takeshi (1985). *Advanced Econometrics*. Harvard University Press: Cambridge, MA.

Bishop, John, John Formby, and Lester Zeager (1996). "The Impact of Food Stamps on US Poverty in the 1980s: A Marginal Dominance Analysis," *Economica*, 63:250, S141-S162.

Bitler, M., J. Currie and J. K. Scholz. 2003. "WIC Eligibility and Participation," *Journal of Human Resources*, 38:S, 1139-1179.

Blundell, Richard and Luigi Pistaferri. 2003. "Income Volatility and Household Consumption" *Journal of Human Resources*, 38:S, 1032-1050.

Bollinger, Christopher and Martin David (1997). "Modeling Discrete Choice with Response Error: Food Stamp Participation." *Journal of the American Statistical Association*, 92 (439) pp. 827-835.

Bollinger and David (2001), Estimation with Response Error and Nonresponse: Food-Stamp Participation in the SIPP, *Journal of Business and Economic Statistics*, 19:2, 129-141.

Bound, John, Charles Brown, and Nancy Mathiowetz (2001), "Measurement Error in Survey Data," in *Handbook of Econometrics. Volume 5*, ed. by J.J Heckman and E. Leamer. Elsevier:

Card, David, Andrew K.G. Hildreth and Lara D Shore-Sheppard (2001), "The Measurement of Medicaid Coverage in the SIPP: Evidence from California 1990-1996" NBER Working Paper 8514.

Cody, S. and C. Tuttle (2002): "The Impact of Income Underreporting in CPS and SIPP on Microsimulation Models and Participating Rates," Washington, D.C.: Mathematica Policy Research, Inc, July 24.

Currie, Janet. 2006. "The Take-up of Social Benefits," in Alan J. Auterbach, David Card, and john M. Quigley, eds. *Public Policy and the Income Distribution*, Russell Sage Foundation: New York.

Fraker, Thomas and Robert Moffitt. 1988. "The Effect of Food Stamps on Labor Supply: a Bivariate Selection Model." *Journal of Public Economics*, February.

Guell, Maria and Luojia Hu. 2006. "Estimating the Probability of Leaving Unemployment Using Uncompleted Spells from Repeated Cross-Section Data, *Journal of Econometrics* 133: 307-341.

Gundersen, Craig and James P. Ziliak. 2003. "The Role of Food Stamps in Consumption Stabilization" *Journal of Human Resources*, 38:S, 1051-1079.

Haider, Steven, Robert Schoeni and Alison Jacknowitz. 2003. "Food Stamps and the Elderly: Why is Participation so Low?" *Journal of Human Resources*, 38:S, 1180-1220.

Hotz, V. Joseph and John Karl Scholz. 2002. "Measuring Employment and Income for Low-Income Populations With Administrative and Survey Data." In Studies of Welfare Populations: Data Collection and Research Issues, eds. Michele Ver Ploeg, Robert A. Moffitt, and Constance F. Citro, 275-313. Washington, DC: National Academy Press.

Jolliffe, Dean, Craig Gundersen, Laura Tiehen, and Joshua Winicki (2005). "Food Stamp Benefits and Child Poverty," *American Journal of Agricultural Economics*, August, 569-581.

Marquis, Kent H. and Jeffrey C. Moore. 1990. "Measurement Errors in SIPP Program Reports." In Proceedings of the 1990 Annual Research Conference, 721-745. Washington, DC.: U.S. Bureau of the Census.

Meyer, Bruce D. and James X. Sullivan. 2003. "Measuring the Well-Being of the Poor Using Income and Consumption." *Journal of Human Resources*, 38:S, 1180-1220.

Meyer, Bruce D., Wallace K.C. Mok, and James X. Sullivan. 2008. "The Underreporting of Transfers in Household Surveys: Its Nature and Consequences" Working Paper.

Meyer, Bruce D. and James X. Sullivan. 2006. "Consumption, Income, and Material Well-Being After Welfare Reform." NBER Working Paper, 11976.

Moore, Jeffrey C., Kent H. Marquis, and Karen Bogen. 1996. "The SIPP Cognitive Research Evaluation Experiment: Basic Results and Documentation." The Survey of Income and Program Participation, Working Paper No. 212. Washington D.C.: U.S. Census Bureau.

Moore, J. C., Stinson, L.L. and Welniak, E. J. Jr. 2000. "Income Measurement Error in Surveys: A Review." Journal of Official Statistics, 14:4, 331-361.

Primus, Wendell, Lynette Rawlings, Kathy Larin, and Kathryn Porter. 1999. "The Initial Impacts of Welfare Reform on the Incomes of Single-Mother Families," Washington, DC: Center on Budget and Policy Priorities.

Roemer, Marc I. 2000. "Assessing the Quality of the March Current Population Survey and the Survey of Income and Program Participation Income Estimates, 1990-1996." Staff Papers on Income, Housing and Household Economic Statistics Division. Washington D.C.: U.S. Census Bureau.

Taeuber, Cynthia, Dean M. Resnick, Susan P. Love, Jane Stavely, Parke Wilde, and Richard Larson. 2004. "Differences in Estimates of Food Stamp Program Participation Between Surveys and Administrative Records" working paper, U.S. Census Bureau.

U.S. Department of Agriculture (USDA). Various Years. "Characteristics of Food Stamp Households: Fiscal Year 2001." Alexandria, VA: The Food and Nutrition Service.

U.S. Department of Agriculture (USDA). 2003. "Trends in Food Stamp Participation Rates." Alexandria, VA: The Food and Nutrition Service.

U.S. General Accounting Office (GAO). 2004. "Food Stamp Program: Steps Have Been Taken to Increase Participation of Working Families, but Better Tracking of Efforts is Needed." GAO-04-346. Washington, DC: GAO.

U.S. Census (2006), "The Effects of Government Taxes and Transfers on Income and Poverty: 2004," February.

U.S. Census (2003), "Codebook for the Current Population Survey: Annual Demographic File, 2002," February.

Zedlewski, S., & Brauner, S. (1999). *Are the steep declines in food stamp participation linked to falling welfare caseloads?* (Series B, No. B-3). Washington, DC: The Urban Institute.

Ziliak, James. 2004. "Filling the Poverty Gap, Then and Now," University of Kentucky Working Paper.

Appendix 1: Data and designating a head of the household in the CPS

Below is the procedure used to designate a household head in the CPS ADF that is comparable to the definition of the head we designate in the FSPQC. In about 95 percent of the households reporting receipt of food stamps in the CPS, this approach will match exactly the approach for the FSPQC (for example, households that include only parents and children, single individual households, or married couple households). However, in a small number of cases (such as households with parents and grandparents present or households with unrelated individuals) the designation of a household head may be somewhat arbitrary.

We designate a head in the CPS as follows:

1. In cases in which there is the presence of a child and the child's parent, the head is defined as the mother of the child (or the father if the mother is not present). If there are multiple children in the household, the head is defined as the mother of the youngest child (or the father if the mother is not present).
2. In households with children in which parents are not present the grandmother is designated as the head (or the grandfather if the grandmother is not present). If grandparents are not present then the head is defined as the head of household (or the wife of the head of the household if the head is a married male).
3. In married couple households the wife is designated as the head.
4. For all remaining households, the principle wage earner among members of the household is designated as the head.

Appendix 2: Alternative Moment Conditions

Now suppose the sampling rate in one of the two datasets is incorrect, so that the w_i are off by a constant. Then the following moment condition augmented by α_1 would still hold

$$\sum_{i \in S} w_i X_i = \sum_{i \in F} w_i X_i \alpha_1 \Lambda(X_i \beta) . \tag{4}$$

Now suppose that some share of non-recipients report receipt and that these people have the same distribution of characteristics X_i as true recipients who report receipt. Such a situation would appear to the researcher as if the weights were off by a scalar so it would yield the same moment condition as (4). This case is close to the situation that occurs when the Census hot-decking procedure is used to impute membership in the subset when it is not reported.

Now consider a different case where some share of non-recipients report receipt and these non-recipients have the same characteristics as the full sample. Thus, the subset can be described as including observations that are not in fact determined through selection process given by Λ, but are automatically included. However, if we modify our earlier moment condition we should be able to obtain consistent estimates in this case. Suppose we solve the modified moment condition

$$\sum_{i \in S} w_i X_i = \sum_{i \in F} w_i X_i [\alpha_1 \Lambda(X_i \beta) + \alpha_2] \ .$$

This should lead to consistent estimates.

In the case where the probability of being in the subset is linear $\Lambda(X\beta) = X\beta$, then only the constant term and the scale of the coefficients would be affected by these misspecifications and the moment condition would not need to be modified to obtain consistent estimates of ratios of elements of β.

Appendix 3: The Univariate Case and Comparisons of the Two Takeup Correction Methods

Using the notation of Section VI, we have from the rules of probability that

$$\bar{x}_S = \frac{\bar{x}_A R_1}{\bar{x}_A R_1 + (1-\bar{x}_A)R_0} \text{ or}$$
$$= \frac{\bar{x}_A R_1}{R}.$$

Rearranging terms we have

$$R_1 = R\frac{\bar{x}_S}{\bar{x}_A},$$

and by symmetry we have

$$R_0 = R\frac{(1-\bar{x}_S)}{(1-\bar{x}_A)}.$$

Differencing these last two expressions gives us

$$(R_1 - R_0) = R\frac{(\bar{x}_S - \bar{x}_A)}{\bar{x}_A(1-\bar{x}_A)}.$$

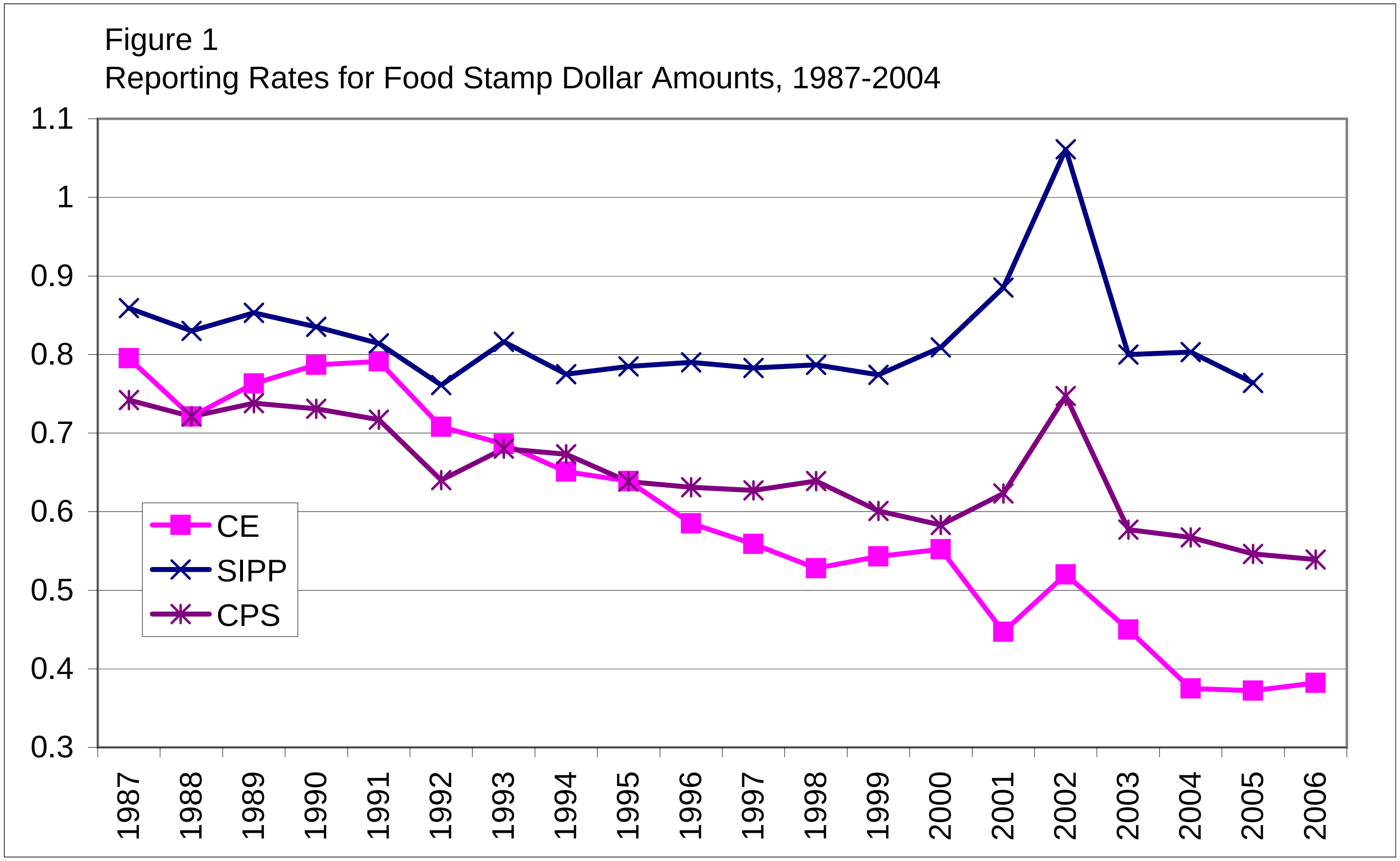
Participation rates corrected for mis-reporting are calculated two ways in the paper. It is worth considering how the two methods differ. Here we write the corrections in the univariate case as a function of observable quantities. Let T_0 be takeup when x=0 and T_1 when x=1. Let $\widetilde{T}_0$ be takeup estimated in the survey data when x=0, and $\widetilde{T}_1$ when x=1. Finally, let $\bar{x}_E$ be the mean of x in the sample of eligibles. Then

$$(T_1 - T_0) = T\frac{(\bar{x}_A - \bar{x}_E)}{\bar{x}_E(1-\bar{x}_E)}$$

is the difference in takeup estimates using our second method, while

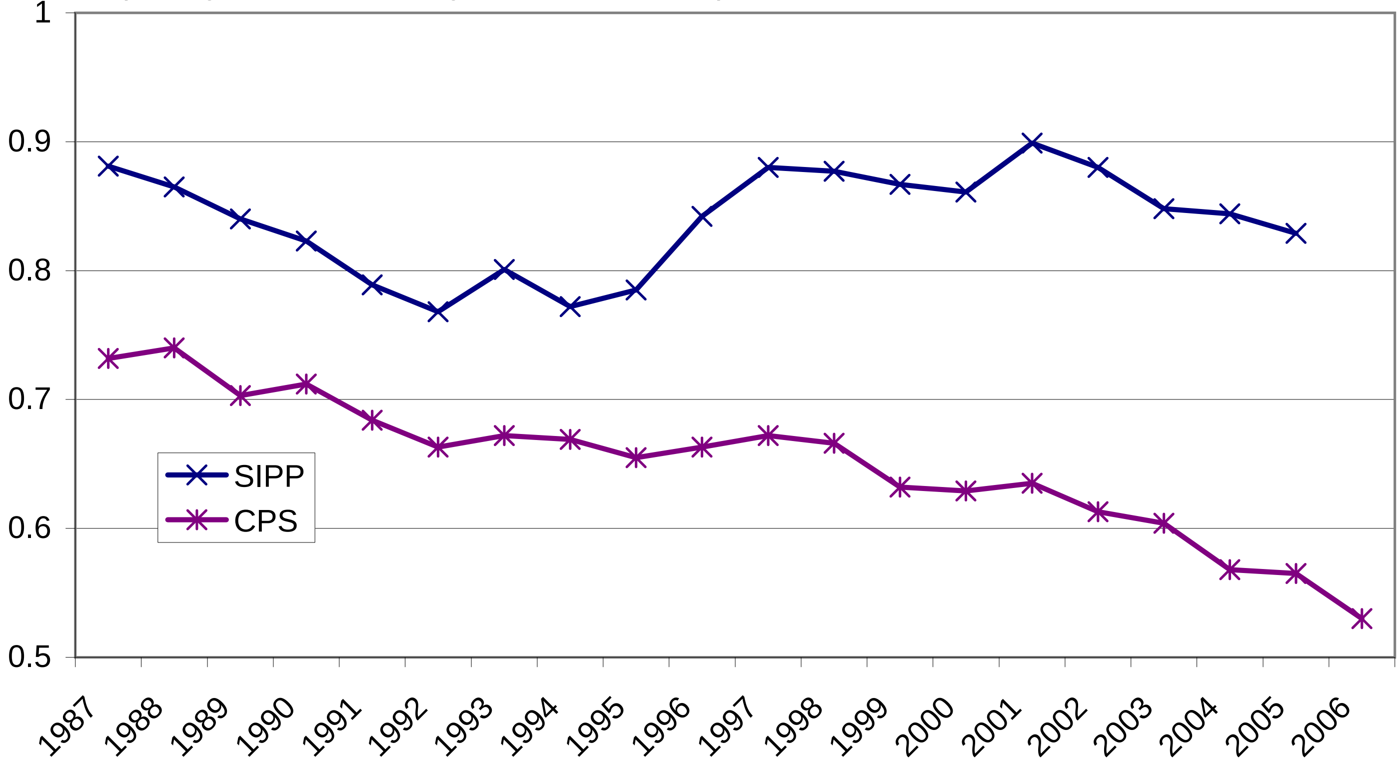
$$\frac{\widetilde{T}_1}{R_0} - \frac{\widetilde{T}_0}{R_1} = \frac{\widetilde{T}_0}{R}\frac{(1-\bar{x}_A)}{(1-\bar{x}_S)} - \frac{\widetilde{T}_1}{R}\frac{\bar{x}_A}{\bar{x}_S}$$

is the same concept estimated using our first method.



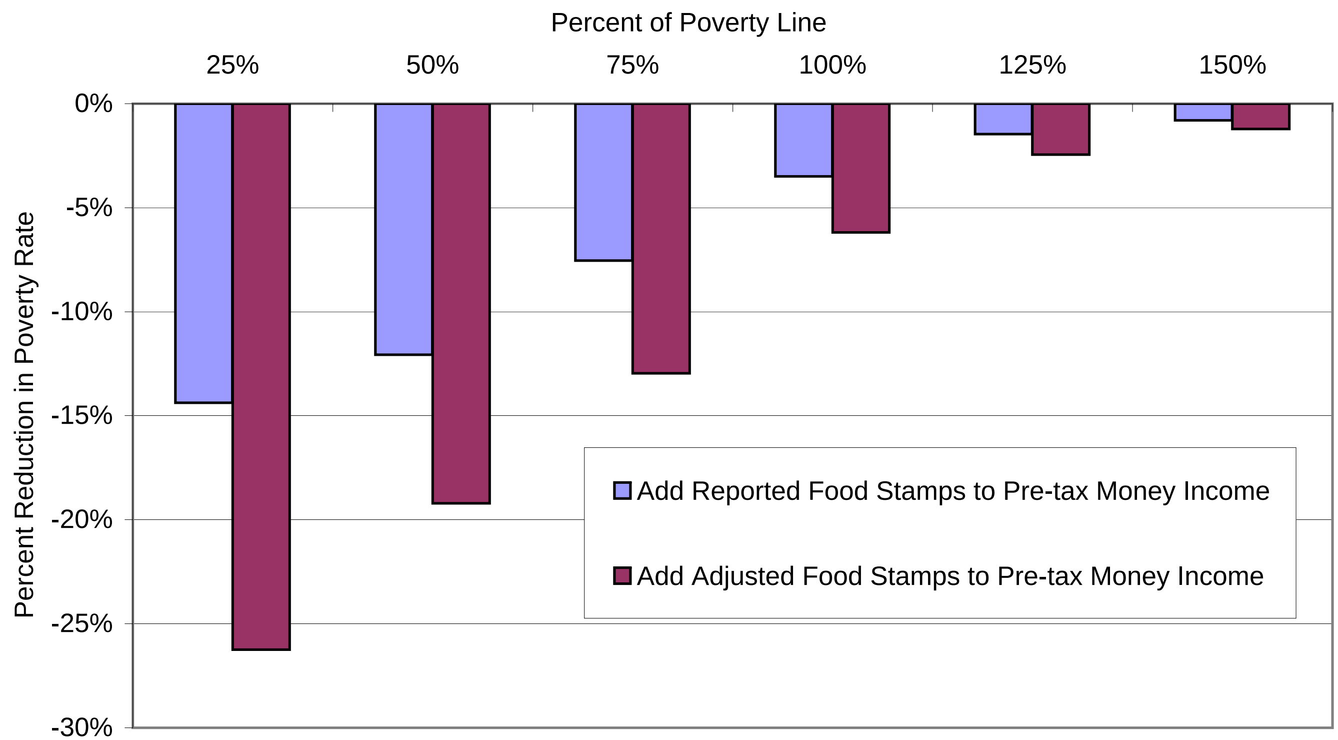
Notes: Data are from Meyer, Mok, & Sullivan (2008). Reporting rates for each year are calculated as the ratio of the total weighted dollars reported for each program in the CPS divided by the respective administrative aggregate. Sources for administrative numbers are reported in Meyer, Mok, and Sullivan (2008).

Figure 2
Reporting Rates for Average Months of Receipt, 1987-2006



Notes: See notes to Figure 1.

Figure 3
The Poverty Reducing Impact of the Food Stamp Program CPS, 2001



Notes: Data are from the 2002 CPS ADF using annual income measures reported for calendar year 2001. For 2001, the fraction with pre-tax income below 25%, 50%, 75%, and 100% of the poverty line were 0.029, 0.048, 0.078, and 0.117 respectively.

Table 1
Demographic Characteristics of the Head of Household, FSPQC and CPS, 2001 Calendar Year, Excluding Imputed Observations

	FSP Quality Control	CPS/ASEC	Difference
	(1)	(2)	(2) - (1)
Age	42.93	42.96	0.030
	(0.080)	(0.269)	(0.280)
U.S. Citizen	0.913	0.916	0.003
	(0.001)	(0.004)	(0.004)
Race (White)	0.466	0.477	0.011
	(0.002)	(0.008)	(0.008)
No High School Degree	0.440	0.425	-0.015*
	(0.003)	(0.008)	(0.008)
Male	0.176	0.159	-0.017*
	(0.002)	(0.006)	(0.006)
South	0.402	0.412	0.009
	(0.002)	(0.008)	(0.008)
West	0.181	0.172	-0.009
	(0.002)	(0.006)	(0.006)
Northeast	0.195	0.194	-0.001
	(0.002)	(0.006)	(0.006)
Midwest	0.222	0.223	0.001
	(0.002)	(0.006)	(0.006)
N	47,266	4,171	

Notes: In the FSPQC, the number of observations is less than 47,266 do to missing values for some characteristics: Age (N=47,174); Citizenship (N=47,063); Race (N=46,628); No High School Degree (N=35,105); Male (N=47,115).

Table 2
Two-Sample Estimates of Under-reporting, FSPQC and CPS, 2001 Calendar Year, Excluding Imputed Observations

	Univariate Results	Multivariate Results				Mean FSPQC Mean CPS
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.552	0.427	0.453	-0.316	0.933	
	(0.057)	(0.190)	(0.191)	(0.210)	(0.510)	
	[0.128]	[0.099]	[0.104]	[-0.071]	[0.207]	
Age	0.000	0.000	0.001	0.017	0.017	42.926
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	42.956
	[0.000]	[-0.000]	[0.000]	[0.004]	[0.004]	
U.S. Citizen	0.105				-1.291	0.913
	(0.192)				(0.474)	0.916
	[0.025]				[-0.232]	
Race (White=1)	0.126	0.133	0.145	0.149	0.233	0.466
	(0.115)	(0.113)	(0.114)	(0.120)	(0.121)	0.477
	[0.029]	[0.031]	[0.033]	[0.033]	[0.052]	
No High School	-0.167			-0.215	-0.279	0.440
Degree	(0.115)			(0.120)	(0.123)	0.425
	[-0.039]			[-0.049]	[-0.062]	
Male	-0.322		-0.368	-0.324	-0.290	0.176
	(0.141)		(0.141)	(0.157)	(0.159)	0.159
	[-0.076]		[-0.087]	[-0.075]	[-0.066]	
South	0.105	0.072	0.058	0.295	0.282	0.402
	(0.117)	(0.145)	(0.146)	(0.144)	(0.146)	0.412
	[0.024]	[0.017]	[0.013]	[0.066]	[0.062]	
West	-0.158	0.206	0.213	0.210	0.096	0.181
	(0.138)	(0.184)	(0.185)	(0.168)	(0.170)	0.172
	[-0.037]	[0.047]	[0.048]	[0.046]	[0.021]	
Northeast	-0.018	0.066	0.070	0.522	0.490	0.195
	(0.142)	(0.171)	(0.172)	(0.194)	(0.197)	0.194
	[-0.004]	[0.015]	[0.016]	[0.112]	[0.104]	
P-Value		0.2222	0.0793	0.0000	0.0000	
N_S	4,171	4,171	4,171	4,171	4,171	
N_A	47,266	46,615	46,612	34,942	34,909	

Notes: ( ) = Standard error; [ ] = average derivative or average discrete difference if variable is binary. For the FSPQC, the number of observations varies across specifications due to missing values for some characteristics (see notes to Table 1).

Table 3
Unadjusted and Adjusted Estimates for Food Stamp Participation Equations, CPS, 2001 Calendar Year, Excluding Imputed Observations

	Unadjusted Logit Estimates	Adjusted Logit Estimates	Unadjusted Logit Estimates	Adjusted Logit Estimates
	(1)	(2)	(3)	(4)
Constant	-0.187		-1.201	
	(0.082)		(0.109)	
	[-0.030]	[-0.065]	[-0.189]	[-0.259]
Age	-0.014		-0.020	
	(0.001)		(0.001)	
	[-0.002]	[-0.002]	[-0.003]	[-0.004]
U.S. Citizen			1.164	
			[0.091]	
			[0.183]	[0.280]
Race (White=1)	-0.403		-0.498	
	(0.050)		(0.053)	
	[-0.065]	[-0.076]	[-0.078]	[-0.096]
No High School Degree			0.607	
			(0.054)	
			[0.095]	[0.116]
Male	-0.364		-0.372	
	(0.071)		(0.072)	
	[-0.059]	[-0.031]	[-0.059]	[-0.037]
South	-0.165		-0.188	
	(0.067)		(0.068)	
	[-0.027]	[-0.031]	[-0.030]	[-0.051]
West	-0.586		-0.421	
	(0.079)		(0.080)	
	[-0.095]	[-0.111]	[-0.066]	[-0.073]
Northeast	-0.104		-0.042	
	(0.078)		(0.079)	
	[-0.017]	[-0.022]	[-0.007]	[-0.043]
N	12,048	12,048	12,048	12,048

Notes: ( ) = Standard error; [ ] = average derivative or average discrete difference if variable is binary. The sample includes all households in the CPS with income below 130 percent of the poverty line. Adjusted estimates in columns 2 and 4 are calculated following the approach in the text using estimates from Table 2.

Table 4
Two-Sample Estimates of Participation, FSPQC and CPS, 2001 Calendar Year, Excluding Imputed Observations

	Univariate Results	Multivariate Results			
	(1)	(2)	(3)	(4)	(5)
Constant	-0.412	1.090	1.121	1.530	-0.014
	(0.021)	(0.085)	(0.086)	(0.101)	(0.109)
	[-0.099]	[0.245]	[0.251]	[0.325]	[-0.003]
Age	-0.018	-0.016	-0.016	-0.028	-0.035
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[-0.004]	[-0.004]	[-0.004]	[-0.006]	[-0.007]
U.S. Citizen	0.629				2.196
	(0.059)				(0.102)
	[0.141]				[0.340]
Race (White=1)	-0.670	-0.639	-0.632	-0.515	-0.907
	(0.043)	(0.047)	(0.047)	(0.052)	(0.065)
	[-0.160]	[-0.147]	[-0.145]	[-0.112]	[-0.183]
No High School	0.524			0.679	0.961
Degree	(0.047)			(0.058)	(0.072)
	[0.127]			[0.147]	[0.190]
Male	-0.242		-0.181	-0.282	-0.319
	(0.051)		(0.055)	(0.060)	(0.067)
	[-0.057]		[-0.040]	[-0.059]	[-0.062]
South	-0.084	-0.452	-0.453	-0.691	-0.741
	(0.042)	(0.064)	(0.064)	(0.073)	(0.082)
	[-0.020]	[-0.100]	[-0.100]	[-0.143]	[-0.141]
West	-0.326	-0.913	-0.912	-1.005	-0.721
	(0.049)	(0.070)	(0.070)	(0.083)	(0.091)
	[-0.076]	[-0.191]	[-0.191]	[-0.197]	[-0.136]
Northeast	0.164	-0.220	-0.217	-0.543	-0.446
	(0.057)	(0.077)	(0.077)	(0.085)	(0.095)
	[0.040]	[-0.048]	[-0.048]	[-0.111]	[-0.085]
P-Value		0.0000	0.0000	0.0000	0.0000
N_S	47,266	46,615	46,612	34,942	34,909
N_A	12,048	12,048	12,048	12,048	12,048

Notes: ( ) = Standard error; [ ] = average derivative or average discrete difference if variable is binary. For the FSPQC, the number of observations varies across specifications due to missing values for some characteristics (see notes to Table 1).

Table A.1
Demographic Characteristics of the Head of Household, FSPQC and CPS, 2001 Calendar Year, Including Imputed Observations

	FSP Quality Control	CPS/ASEC	Difference
	(1)	(2)	(2) - (1)
Age	42.93	44.40	1.475*
	(0.080)	(0.249)	(0.262)
U.S. Citizen	0.913	0.916	0.002
	(0.001)	(0.004)	(0.004)
Race (White)	0.466	0.475	0.009
	(0.002)	(0.007)	(0.008)
No High School Degree	0.440	0.419	-0.021*
	(0.003)	(0.007)	(0.008)
Male	0.176	0.153	-0.023*
	(0.002)	(0.005)	(0.006)
South	0.402	0.409	0.007
	(0.002)	(0.007)	(0.007)
West	0.181	0.170	-0.010
	(0.002)	(0.005)	(0.006)
Northeast	0.195	0.197	0.003
	(0.002)	(0.006)	(0.006)
Midwest	0.222	0.223	0.001
	(0.002)	(0.006)	(0.006)
N	47,266	4,770	

Notes: In the FSPQC, the number of observations is less than 47,266 do to missing values for some characteristics: Age (N=47,174); Citizenship (N=47,063); Race (N=46,628); No High School Degree (N=35,105); Male (N=47,115).

Table A.2
Two-Sample Estimates of Reporting Rate, FSPQC and CPS, 2001 Calendar Year, Including Imputed Observations

	Univariate Results	Multivariate Results				Mean FSPQC Mean CPS
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.552	0.336	0.369	-0.409	0.987	
	(0.053)	(0.181)	(0.183)	(0.205)	(0.532)	
	[0.128]	[0.078]	[0.085]	[-0.091]	[0.216]	
Age	0.003	0.002	0.003	0.021	0.021	42.926
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	44.401
	[0.001]	[0.001]	[0.001]	[0.005]	[0.005]	
U.S. Citizen	0.049				-1.444	0.913
	(0.185)				(0.501)	0.916
	[0.011]				[-0.249]	
Race (White=1)	0.114	0.111	0.127	0.121	0.214	0.466
	(0.108)	(0.107)	(0.108)	(0.115)	(0.115)	0.475
	[0.026]	[0.026]	[0.029]	[0.027]	[0.047]	
No High School	-0.210			-0.278	-0.349	0.440
Degree	(0.108)			(0.114)	(0.118)	0.419
	[-0.049]			[-0.062]	[-0.077]	
Male	-0.405		-0.466	-0.442	-0.406	0.176
	(0.129)		(0.130)	(0.147)	(0.149)	0.153
	[-0.096]		[-0.111]	[-0.101]	[-0.091]	
South	0.080	0.048	0.030	0.270	0.256	0.402
	(0.110)	(0.136)	(0.137)	(0.137)	(0.138)	0.409
	[0.019]	[0.011]	[0.007]	[0.060]	[0.056]	
West	-0.188	0.180	0.188	0.190	0.065	0.181
	(0.130)	(0.173)	(0.174)	(0.161)	(0.163)	0.170
	[-0.044]	[0.041]	[0.043]	[0.041]	[0.014]	
Northeast	0.047	0.106	0.112	0.585	0.554	0.195
	(0.135)	(0.162)	(0.164)	(0.189)	(0.192)	0.197
	[0.011]	[0.024]	[0.026]	[0.123]	[0.115]	
P-Value		0.0034	0.0007	<0.0001	<0.0001	
N_S	4,770	4,770	4,770	4,770	4,770	
N_A	47,266	46,615	46,612	34,942	34,909	

Notes: ( ) = Standard error; [ ] = average derivative or average discrete difference if variable is binary. For the FSPQC, the number of observations varies across specifications due to missing values for some characteristics (see notes to Table 1).

Table A.3
Unadjusted and Adjusted Estimates for Food Stamp Participation Equations, CPS, 2001 Calendar Year, Including Imputed Observations

	Unadjusted Logit Estimates	Adjusted Logit Estimates	Unadjusted Logit Estimates	Adjusted Logit Estimates
	(1)	(2)	(3)	(4)
Constant	-0.231		-1.163	
	(0.077)		(0.102)	
	[-0.037]	[-0.066]	[-0.184]	[-0.256]
Age	-0.014		-0.019	
	(0.001)		(0.001)	
	[-0.002]	[-0.002]	[-0.003]	[-0.004]
U.S. Citizen			1.054	
			(0.084)	
			[0.166]	[0.273]
Race (White=1)	-0.406		-0.480	
	(0.047)		(0.049)	
	[-0.066]	[-0.075]	[-0.076]	[-0.092]
No High School Degree			0.575	
			(0.050)	
			[0.091]	[0.116]
Male	-0.414		-0.425	
	(0.067)		(0.068)	
	[-0.067]	[-0.031]	[-0.067]	[-0.037]
South	-0.122		-0.143	
	(0.062)		(0.063)	
	[-0.020]	[-0.022]	[-0.023]	[-0.042]
West	-0.538		-0.387	
	(0.074)		(0.076)	
	[-0.087]	[-0.101]	[-0.061]	[-0.066]
Northeast	-0.102		-0.042	
	(0.072)		(0.073)	
	[-0.017]	[-0.025]	[-0.007]	[-0.048]
N	13,905	13,905	13,905	13,905

Notes: ( ) = Standard error; [ ] = average derivative or average discrete difference if variable is binary. The sample includes all households in the CPS with income below 130 percent of the poverty line. Adjusted estimates in columns 2 and 4 are calculated following the approach in the text using estimates from Table 2.

Table A.4
Two-Sample Estimates of Participation, FSPQC and CPS, 2001 Calendar Year, Including Imputed Observations

	Univariate Results	Multivariate Results			
	(1)	(2)	(3)	(4)	(5)
Constant	-0.412	1.052	1.083	1.492	-0.024
	(0.020)	(0.079)	(0.080)	(0.094)	(0.103)
	[-0.099]	[0.236]	[0.243]	[0.317]	[-0.005]
Age	-0.019	-0.016	-0.016	-0.028	-0.035
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[-0.004]	[-0.004]	[-0.004]	[-0.006]	[-0.007]
U.S. Citizen	0.571				2.117
	(0.057)				(0.097)
	[0.129]				[0.331]
Race (White=1)	-0.686	-0.631	-0.624	-0.503	-0.862
	(0.041)	(0.044)	(0.044)	(0.049)	(0.061)
	[-0.164]	[-0.145]	[-0.144]	[-0.109]	[-0.175]
No High School	0.548			0.708	0.974
Degree	(0.045)			(0.056)	(0.069)
	[0.132]			[0.154]	[0.194]
Male	-0.229		-0.172	-0.280	-0.315
	(0.049)		(0.052)	(0.057)	(0.063)
	[-0.054]		[-0.038]	[-0.059]	[-0.061]
South	-0.026	-0.351	-0.353	-0.590	-0.623
	(0.040)	(0.059)	(0.059)	(0.068)	(0.075)
	[-0.006]	[-0.078]	[-0.078]	[-0.122]	[-0.120]
West	-0.293	-0.826	-0.826	-0.914	-0.632
	(0.047)	(0.066)	(0.066)	(0.078)	(0.085)
	[-0.069]	[-0.175]	[-0.175]	[-0.181]	[-0.120]
Northeast	0.081	-0.240	-0.239	-0.563	-0.466
	(0.052)	(0.070)	(0.070)	(0.078)	(0.087)
	[0.019]	[-0.053]	[-0.053]	[-0.115]	[-0.089]
P-Value		0.0000	0.0000	0.0000	0.0000
N_S	47,266	46,615	46,612	34,942	34,909
N_A	13,905	13,905	13,905	13,905	13,905

Notes: ( ) = Standard error; [ ] = average derivative or average discrete difference if variable is binary. For the FSPQC, the number of observations varies across specifications due to missing values for some characteristics (see notes to Table 1).