The Working Poor--A Statistical Artifact?

By

Marlene Kim
Dept. Of Labor Studies and Employment Relations
SMLR
50 Clifton Avenue
Rutgers University
New Brunswick, NJ 08901
Voice: (732) 932-1747
Fax: (732) 932-8677
Email: mrlkim@rci.rutgers.edu

Catherine J. Weinberger
Department of Economics and
Institute for Social, Behavioral and Economic Research
University of California, Santa Barbara
Santa Barbara, CA 93106
Email: weinberg@isber.ucsb.edu

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We examine the effect of measurement error on estimates of the size of the working poor population. Using a unique data set, which includes both self-reported and employer-reported earnings, we find that inaccurately reported earnings are common. Among those with very low self-reported earnings are many individuals with underreported earnings. However, this is offset by a high incidence of overreporting among those who actually have low earnings. We find that, by fortunate coincidence, these counterbalancing sources of measurement error cancel each other out exactly. This result is robust to changes in the designated poverty threshold.

The Working Poor--A Statistical Artifact?

Introduction

For many Americans, there is something immoral about the very existence of the working poor. Because most people believe that hard work should be rewarded with earnings that bring one above the poverty level, the existence of 9 million Americans who work but remain poor seems wrong. So wrong, in fact, that some scholars have suggested that estimates of the size of the working poor population are greatly exaggerated.

For example, Murray (1987) describes case studies of families who have current incomes below the official poverty threshold, but are not poor. Bradley Schiller (1994) believes that the Current Population Survey (CPS), the data set usually used to estimate the working poor population, overestimates the number of the working poor because of the way the survey is conducted. Rather than reporting current earnings, surveyed individuals must recall earnings over the past fifteen months. This is likely to produce a fair bit of error.[1] Despite claims that the measurement error that results overestimates the size of the working poor population, no one has investigated whether this indeed occurs.

We use a unique data set to examine the effect of measurement error on estimates of the working poor population. Because the data set includes each individual's self-reported earnings in the CPS as well as the earnings reported by their employers to the Social Security Administration (SSA), the exact error in CPS earnings can be estimated for each person in the sample. We find that, surprisingly, measurement error does not bias estimates of the working poor population. Although some of those who have low reported earnings underreport their earnings, an equally large number of low earners overreport their earnings. By fortunate coincidence, these two sources of measurement error cancel each other out. The number of people who fall below the poverty line is exactly the same whether one uses self-reported or employer-reported earnings.

The Data

The data set used in this analysis was compiled by Bound and Krueger (1991) in order to examine the extent of measurement error in annual earnings reported in the CPS's Annual Demographic files. The Annual Demographic Files include a random sample of a cross section of approximately 50,000 households in the U.S. and contain information such as the annual earnings (from the previous calendar year) of each individual in each household. The subsample constructed by Bound and Krueger (1991) includes a sample of individuals surveyed in both 1977 and 1978,

[1] Schiller (1994) also believes that additional measurement error is introduced because only one person reports the earnings of all members in a household. However, Bound and Krueger (1991) find that self reported earnings are as reliable as such proxy responses.

matched to the annual earnings that their *employers* reported to the Social Security Administration (SSA). This match was possible because during the 1978 survey, some individuals were asked their Social Security Numbers. This information was used to find the annual earnings that their employers reported to the Social Security Administration.

We used the exact sample described by Bound and Krueger (1991). This sample includes 4021 heads of households, 3463 men and 556 women. Bound and Krueger restricted the sample to those who were employed in a SSA covered job in both 1976 and 1977, who had positive values of both CPS earnings and SSA earnings in both years, and who made consistent reports about their age, sex, education, and race in the two years they were surveyed. This sample has demographic characteristics similar to those in the full CPS sample during these years, but somewhat higher reported CPS earnings than the full CPS sample. Bound and Krueger speculate that their higher earnings are the result of restricting the sample to individuals with employment in covered jobs for at least parts of two consecutive years (Bound and Krueger, 1991). Bollinger (1998) finds that the members of the Bound and Krueger sample are somewhat less prone to overreporting earnings compared to a representative sample.

In order to maximize the number of observations, we used the self-reported and employer-reported earnings of all 4021 people in both years, which resulted in 8042 observations. 1976 earnings were converted to their 1977 dollar equivalents. Employer-reported SSA earnings were top-coded at the taxable maximum for Social Security, which was $16,500 in 1977 and $15,300 in 1976.[2]

Measurement Error in Reported Earnings

Measurement error in earnings is defined as the difference between an individual's reported earnings and his or her true earnings. Following Bound and Krueger (1991), we define reported earnings as the self-reported CPS earnings and true (or actual) earnings as the earnings that were reported to the SSA by that individual's employer or employers.

If Y_{REP} denotes reported (CPS) earnings and Y_{TRUE} denotes true (SSA) earnings, the amount of measurement error, E, is the difference between these:

$$E = Y_{REP} - Y_{TRUE} \qquad \text{Equation 1}$$

E is defined for all individuals whose true earnings are not top-coded. Notice that $E > 0$ for people

[2] Of the 6926 observations for men, 4379 had earnings that were not top-coded. Of 1112 observations for women, 1068 had earnings that were not top-coded. Since we are studying the lowest earners, the lack of information on those with very high employer-reported earnings is of little consequence to our analysis

who overreport their earnings, and E < 0 for people who underreport their earnings.[3]

The existing literature provides us with two expected sources of measurement error in estimating the working poor population. The first is the systematic overreporting of earnings by people with low true earnings. Bound and Krueger (1991) observed that the amount of measurement error is negatively correlated with true earnings, or "mean-reverting." Most of this correlation can be explained by the tendency of those with the lowest earnings, who include the working poor, to overreport their earnings by a large amount (Bollinger, 1998). The systematic tendency of low earners to overreport their earnings (which we call systematic error[4]) will bias estimates of the working poor population based on reported earnings downwards.

However, there is a countervailing effect as well, caused by random errors.[5] Among those with low reported earnings, there is likely to be a disproportionate number of individuals who have underreported earnings.[6] Example 1 illustrates this. Suppose that out of 100 people, half earn $10 and half earn $20, and that at each level of earnings, half the people underreport their earnings by $5 and half overreport their earnings by $5. Therefore, one quarter report earning $5, one half report earning $15, and one quarter report earning $25.

* Example 1 about here *

At both levels of true earnings the average error is 0, so there is no systematic error, only random error. At the mean of the reported earnings, $15, the average error is also 0. But at low reported earnings ($5), the average error is negative (-$5). Although a quarter of the people report that they earn $5, none actually earn an amount this low. The tendency for negative random error to accumulate in the lower tail of the reported earnings distribution will bias estimates of the working poor population upwards.

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[3] In this sample, overreporting is more common than underreporting: Among people with earnings below the SSA maximum, 49% overreported their earnings, while only 39% underreported. This tendency is even more pronounced among people with true earnings less than $6000. Among these low earners, 57% overreported their earnings, while only 30% underreported.
[4] Systematic errors do not average away as more measurements are taken. The classic example used to describe systematic error in physics is taking measurements with a ruler that expands or contracts with changes in temperature (Bevington and Robinson, 1992; Press, 1994). If the room is cold, the ruler will shrink and overstate the length of anything measured, even if many measurements are taken and averaged together.
[5] Random error is the type of error that is commonly studied in statistics or econometrics. It has mean zero and variance that diminishes as the sample size is increased (Bevington and Robinson, 1992; Press, 1994).
[6] Friedman was the first to notice this phenomenon when he noted that "the winner in any particular set of races may well be better on the average than the losers but they are also likely to have had more than their share of good luck" (Friedman, 1957: 35). The reverse is also true: the loser of any particular set of races will more likely be slower than the average but also have had his or her share of bad luck. In other words, at the tails of any distribution, the average random error will be non-zero. Thus individuals with very low reported earnings are likely to have both low true earnings *and* reported earnings that are below their true earnings.

In Example 2, we generalize this illustration to allow for systematic as well as random error. There is systematic error because, on average, people overreport their earnings by S. The random error retains the same structure as in Example 1, with half of the people reporting true earnings plus S+5, and half true earnings plus S-5. Notice that if S=0, then this example is identical to Example 1. In Example 2, one quarter report earning S+$5, one half report earning S+$15, and one quarter report earning S+$25. At the lowest value of reported earnings (S+$5), the average amount of measurement error (S-$5) is negative if S is small (S < 5), positive if S is big (S > 5), and zero if S = 5. In other words, if people, on average, overstate their earnings by a large amount, even those with low reported earnings will have reported earnings greater than true earnings (positive mean error).

In the real world, the combination of these two effects may lead to either an undercount of the working poor (if the systematic tendency to overreport earnings predominates) or to an overcount of the working poor (if there is a strong concentration of negative measurement error among those with low reported earnings). Our analysis aims to measure the relative and net effects of these two sources of measurement error. We first estimate the relative contributions of systematic and random error to the error term observed at different levels of reported earnings. We then examine how poverty rates computed from reported earnings compare with poverty rates computed from true earnings. Because Bound and Krueger (1991) found that the amount of measurement error was different for men than for women, we performed all analyses separately by sex.

Modeling the Components of Error

In this section we introduce more formal descriptions of the systematic and random components of error. Recall that:

$$E = Y_{REP} - Y_{TRUE} \qquad \text{Equation 1}$$

Measurement error is composed of a systematic (SE) and a random component (RE):

$$E=SE+RE \qquad \text{Equation 2}$$

By definition, systematic error (SE) is the mean error at a given level of true earnings. At a given level of true earnings, random error (RE) is a random variable with mean zero, and the same variance (and higher moments) as E.

To keep the analysis as simple but accurate as possible, we estimate systematic error as the average of E among those with similar true earnings.[7] For example, if Y_{TRUE_i} = \$3,300, then our estimate of systematic error ($\hat{S}E_i$) equals the average of E for all observations with Y_{TRUE} between \$2500 and \$3500.

We estimate random error as:

$$\hat{R}E_i = E_i - \hat{S}E_i \qquad \text{Equation 3}$$

Note that because random error measures deviations from the average amount of error, the existence of negative random error does not necessarily indicate underreporting.

Table 1 reports estimates of the amount of total error, systematic error, and random error at different levels of true earnings. As expected, there is mean reverting error: the total amount of error and systematic error are positive for low values of true earnings and decrease in true earnings. For those with the lowest true earnings, reported earnings are substantially higher (on average) than true earnings. For example, men who actually earn between \$500 and \$5000 overreport their earnings by \$1413 on average, while those who earn between \$5000 and \$10,000 overreport their earnings by \$631.

* Table 1 about here *

Table 2 reports estimates of the total error, systematic error, and random error at different levels of reported earnings.[8] As expected, there is a large amount of negative random error, especially among those with low reported earnings. For example, among men with reported earnings between \$500 and \$5000, the average of random error is -\$2171, compared to a mean error of -\$908. In other words, men with low reported earnings tend to report earnings \$908 less than what they actually made. But, compared to other men with the same true earnings, they are reporting \$2171 less. Because many people who actually have low earnings overreport their earnings, total error is far less negative than random error.

* Table 2 about here *

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[7] Formally, $\hat{S}E_i = \underset{j \in J}{mean}(E_j)$ s.t. $Y_{TRUE_i} \in J$

Where:

i indexes individuals

J indexes Y_{TRUE} intervals (0-500, 500-1500, 1500-2500, 2500-3500, . . .)

j indexes individuals in J

[8] In Table 2, the results are reported only for those with reported earnings below \$10,000. At higher levels of reported earnings, many had censored true earnings. Since we are interested in those with low earnings, this omission is of little consequence to our analysis.

Estimating the Number of Low Earners

Now that we have examined the composition of measurement error in this data set, we turn to the motivating question: How does this error affect estimates of poverty? Because there is negative mean error at low levels of reported earnings (mean reported earnings less than mean true earnings), we might expect that poverty estimates using reported earnings will be slightly higher than poverty estimates using true earnings. However, this is not necessarily the case. Bias in poverty rates depends not only on the distribution of error among those with low reported earnings, but also on the number of observations with low true but high reported earnings. The observations with low true but high reported earnings are, of course, not included in the estimate of mean error among those with low reported earnings.[9]

In this section, we compare the proportion of observations with *reported* earnings below a given threshold with the proportion with *true* earnings below that threshold. The difference between these estimates informs us whether, or how, using reported earnings instead of true earnings biases estimates of the working poor population. We examine these results at various earnings thresholds, starting at $500 and increasing in $500 increments up to $10,000. Thus these thresholds are not limited to the official poverty thresholds, which in 1977 were $6157 for a family of four and $3,067 for a family of one, but include many alternative thresholds.

The surprising results can be seen in Table 3 and Graphs 1 and 2. Reported earnings are an extremely accurate proxy for true earnings when computing the proportion of a population with earnings below a given threshold. At every earnings threshold, for both men and women, the estimated proportions are virtually identical. Where there are differences approaching one standard deviation, reported earnings slightly underestimate poverty rates. In no case is the difference statistically significant. Due to a fortunate coincidence, the systematic and random errors in reported earnings cancel each other out among those with low earnings.

* Table 3, Graphs 1, 2 about here *

Thus, for both men and women, CPS earnings data lead to accurate estimates of the working poor population. A closer look reveals the following: Of 6939 men in the sample, 453 have both true and reported earnings less than $6000.[10] In addition, 120 men with true earnings above $6000 report earning less than $6000, while 119 men report earning at least $6000 but actually earn less.

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[9] An additional factor to consider is the characteristics of E other than its mean. For example, consider a group of people with reported earnings just below the poverty line. Suppose we know that there is negative average error, so that these people have average true earnings slightly above the poverty line. This group may be composed entirely of people who have true earnings just above the poverty line. Alternatively, the group may be composed of many people whose actual earnings are below the poverty line plus a few people with very high true earnings, pulling the average above the poverty line. Reported earnings suggest that all of these people are in poverty. In the first case, none of these people are actually below the poverty line. In the second case, most of these people's actual earnings are below the poverty line.

[10] $6000 is close to the poverty line for a family of four in 1977 ($6157).

Therefore, whether we use true or reported earnings to compute the proportion of men with earnings less than $6000, we obtain the same result-- 8.3%. Similarly, of 1110 women in the sample, 351 have both true and reported earnings below $6000; 44 report earning less than $6000 but actually earn more, and 46 report earning more than $6000 but actually earn less. Again, the positive and negative errors cancel out.

This analysis illustrates an important point: Murray (1987) supports his argument that few families fall into the working poor category by giving examples of individual families with current incomes below the poverty line who are not, according to our usual sense of the word, poor. Yet defining an earnings threshold for purposes of estimating a summary statistic is entirely different from defining criteria for purposes of determining eligibility for program participation. In the previous example, 26% of the men reported earning less than $6000 but actually earned more than $6000. For purposes of statistical estimation, however, this fact is of no consequence, since there was an equal number of people who earned less than $6000 but reported earning more than $6000.

When an individual or family is evaluated for program eligibility, it is customary and appropriate to require detailed information about that family's assets and expenses as well as earnings. Programs are, and should be, designed to target those who meet specific selection criteria for need. By contrast, it would be costly, intrusive and unnecessary to collect detailed information in order to estimate a summary statistic. In this case, it is necessary only to define an earnings threshold such that, on average, there are as many families who are actually poor with earnings above the threshold as families who are actually non-poor with earnings below the threshold. The power of statistics is that, with a large enough sample, these errors cancel out.

Uncovered Earnings

Because of the limitations of the data available to us, these estimates have been restricted to those with SSA covered employment. It is likely that low earners, especially very low earners, receive income from uncovered jobs: under-the-table income from baby-sitting, for example, or illegal jobs such as drug dealing (Edin, 1993; Edin and Lein, 1997). The earnings from these uncovered jobs are not included in our measure of true earnings. In addition to underreported earnings from uncovered employment, there is likely to be other unreported income as well. Gifts or emergency loans from family or friends can be another source of income for low earners that may or may not be included in the incomes measures of the CPS. To our knowledge, no data exist that will allow us to examine these sources of error.

But qualitative analysis suggests that these unreported earnings are unlikely to affect estimates of the number of people who are poor. Edin (1993) and Edin and Lein (1997) found that all of the welfare mothers they interviewed in Chicago were employed. Their earnings, which were not reported to government officials, comprised 21% of their income. An additional 21% of income came from gifts from friends, boyfriends, relatives, absent fathers, and charity. But because these women were so poor, this additional income supplemented their AFDC payments so that they were still well below the poverty threshold (Jencks and Edin, 1995). If these findings hold more generally, it is likely that few people have enough unreported earnings to lift them out of poverty. Obviously, future research should examine this subject more thoroughly.[11]

More Recent Years

Although our analysis is based on 1976 and 1977 earnings, we can make reasonable inferences about the pattern of measurement error in more recent years. Both the random and systematic error we have investigated are the result of both human nature (e.g. exaggerating earnings, clerical errors, forgetfulness) and statistical properties of the earnings distribution. There is no evidence that human nature has changed, and recent research on the distribution of earnings informs us about the likely direction of changes in measurement error.

The well-documented increase in earnings dispersion (see e.g. Levy and Murnane, 1992) over the last twenty years is likely to have affected the mean-reverting systematic error. If mean-reverting error results from the tendency of poor people to report higher than actual earnings in order to seem more "normal," the average amount of systematic overreporting among the poor is likely to have increased, since the difference between median earnings and the actual earnings of low-income workers is now greater. Thus, the increased earnings dispersion observed over the past 20 years has probably led to an increase in the magnitude of systematic overreporting among low-earners and an undercount of the working poor population.

The effect of the changing earnings distribution on random errors is harder to predict. In 1976 and 1977, the combination of systematic and random error led to the same number of people crossing the poverty line in one direction as in the other. In the current time period, we would obtain these same results only if there is an increase in negative random error that compensates for the increase in positive systematic error. With no reason to expect such an increase, we suspect that more recent data will slightly underestimate poverty rates.

[11] Those with incomes close to the poverty line could be lifted above poverty. However, if the people who assist these low earners are close to the poverty line themselves, the net effect could be no change in the poverty rate, if such gifts or loans push the gift-givers below poverty. More research needs to be performed to examine this issue.

Conclusion

Many scholars believe that the official poverty rate does not adequately measure the number of those who should be considered poor (see Cito and Michael, 1995, for a nice summary of this debate). In part, this is caused by the definition of poverty, which overlooks the resources and special needs that should be considered in assessing whether or not someone is poor. In addition, others argue that even if we could agree upon a definition of poverty and the resources that are counted in one's poverty status, there is substantial measurement error in the most popular data bases used to estimate the poor. Usually, those who argue that the present measure underestimates poverty believe that the official poverty threshold requires people to live on an unreasonably small amount of money, and that expenses like taxes and large medical expenses should be excluded from the resources available to a family. Others, however, claim that the estimates of the poor are overstated because in-kind benefits such as food stamps are not included in the resources available to the poor and that the poor understate their earnings. Although previous research has examined the problem of defining the poor and underreported income, no one has examined whether estimates of the working poor are too large because of error in measuring earnings. This latter claim has gone unquestioned until now.

This paper analyzed two opposing sources of measurement error in estimating the number of people with low earnings. The first is the tendency of those with low earnings to overstate their earnings in survey data. The second is the statistical probability that, on average, those with the lowest reported earnings have higher-than-reported true earnings. We found that both of these effects are large but they cancel out. Thus, poverty rates calculated from CPS self-reported earnings are highly accurate. Although as critics state, some people underreport their earnings, a counterbalancing group overstate their earnings. The net effect is an extremely accurate estimate of the working poor population.

These results are quite robust. They hold over a broad range of earnings thresholds, not just at the official poverty line. Thus, even if policy makers decide that the official poverty line is either too high or too low, these results will still hold. No matter what earnings threshold is used to measure poverty, one obtains a statistically accurate measure of the poverty rate when using CPS self-reported earnings. Measurement error from inaccurately recalling one's earnings or from recalling the earnings of others in one's household does not lead to error in measuring the number of people who are poor. Researchers of poverty can rest assured that government estimates of the working poor population, based on the widely-used CPS data sets, are not as biased as once believed.

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Example 1 -- The Distribution of Mean Error with No Systematic Error

True Earnings (Y_{TRUE})	Reported Earnings (Y_{REP})	Error $E=(Y_{REP} - Y_{TRUE})$	Mean of E by Y_{TRUE}	Mean of E by Y_{REP}	Number of Cases (N)
10	5	-5	0	-5	25
	15	+5		0	25
20	15	-5	0		25
	25	+5		+5	25

Example 2 -- The Distribution of Mean Error with Positive Systematic Error

True Earnings (Y_{TRUE})	Reported Earnings (Y_{REP})	Error $E=(Y_{REP} - Y_{TRUE})$	Mean of E by Y_{TRUE}	Mean of E by Y_{REP}	Number of Cases (N)
10	5+S	-5+S	0+S	-5+S	25
	15+S	+5+S		0+S	25
20	15+S	-5+S	0+S		25
	25+S	+5+S		+5+S	25

Table 1 -- The Components of Error at Different Levels of True Earnings

MEN	Y_{TRUE} < \$500	Y_{TRUE} \$500-\$4999	Y_{TRUE} \$5000-\$9999	Y_{TRUE} \$10,000+
Mean Error (Standard Deviation)	2104 (5061)	1413 (3303)	631 (2383)	67 (2057)
Mean Systematic Error	2104	1417	622	70
Mean Random Error / S.D. of Random Error	0.00	-0.00	0.00	-0.00
N	22	410	1140	2603
WOMEN				
Mean Error (Standard Deviation)	1586 (3850)	483 (1688)	258 (1620)	-291 (1962)
Mean Systematic Error	1586	437	280	-283
Mean Random Error / S.D. of Random Error	0.00	0.03	-0.01	-0.00
N	17	286	491	269

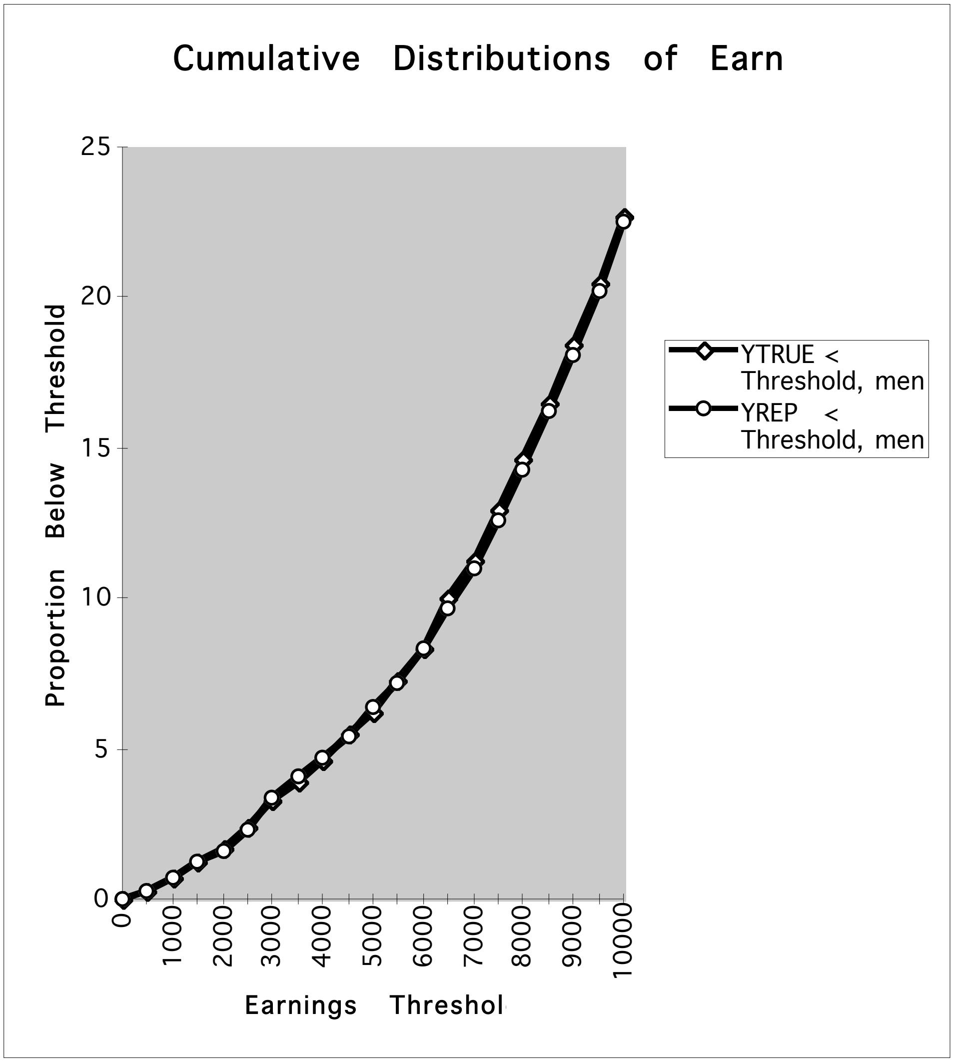
Table 2-- The Components of Error at
Different Levels of CPS Self-Reported Earnings

	Y_{REP} < \$500	Y_{REP} \$500-\$4999	Y_{REP} \$5000-\$9999
MEN			
Mean Error (Standard Deviation)	-2909 (4757)	-908 (2703)	-256 (1917)
Mean Systematic Error	1576	1263	600
Mean Random Error	-4486	-2171	-856
Mean Random Error /S.D. of Random Error	-1.13	-0.91	-0.49
N	19	415	1079
WOMEN			
Mean Error (Standard Deviation)	-1691 (4285)	-233 (1208)	150 (1387)
Mean Systematic Error	991	433	258
Mean Random Error	-2682	-666	-107
Mean Random Error /S.D. of Random Error	-0.77	-0.57	-0.08
N	20	279	483

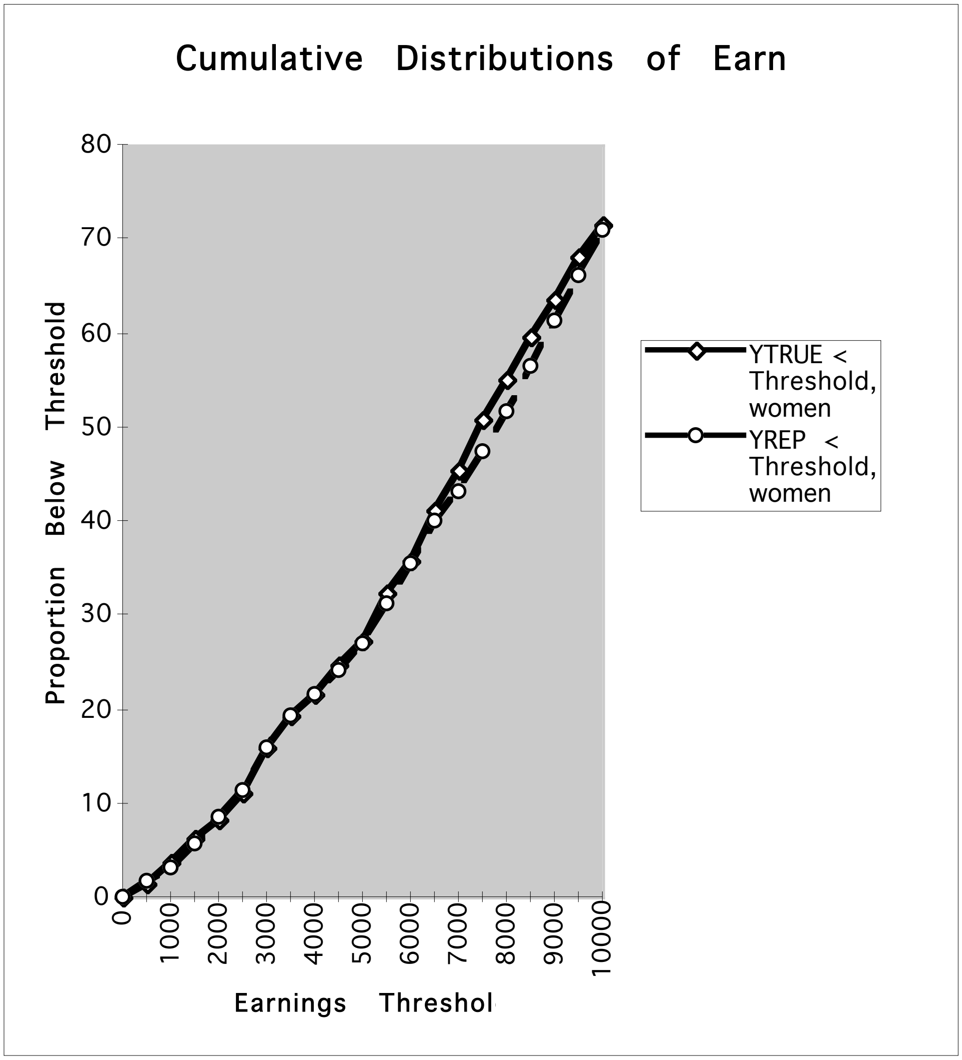
Table 3--Cumulative Distributions of CPS Self-Reported Earnings and of SSA Employer-Reported Earnings (Percentage of Men and of Women with Earnings Below Designated Threshold. Standard Errors in Parentheses.)

	MEN (N=6932)		WOMEN (N=1110)	
	True Earnings	CPS Earnings	True Earnings	CPS Earnings
Percent with Earnings Less Than:				
$500	0.32 (.07)	.27 (.06)	1.53 (.39)	1.80 (.40)
$1000	.69 (.10)	.71 (.10)	3.60 (.56)	3.06 (.52)
$1500	1.20 (.13)	1.20 (.13)	6.13 (.72)	5.68 (.69)
$2000	1.70 (.16)	1.60 (.15)	8.11 (.82)	8.65 (.84)
$2500	2.39 (.18)	2.26 (.18)	11.17 (.95)	11.35 (.95)
$3000	3.26 (.21)	3.39 (.22)	15.77 (1.09)	15.77 (1.09)
$3500	3.94 (.23)	4.07 (.24)	19.28 (1.18)	19.37 (1.19)
$4000	4.62 (.25)	4.67 (.25)	21.53 (1.23)	21.71 (1.24)
$4500	5.54 (.27)	5.37 (.27)	24.68 (1.29)	24.23 (1.29)
$5000	6.23 (.29)	6.38 (.29)	27.30 (1.34)	27.03 (1.33)
$5500	7.30 (.31)	7.24 (.31)	32.16 (1.40)	31.08 (1.39)
$6000	8.28 (.33)	8.27 (.33)	35.68 (1.44)	35.50 (1.44)
$6500	10.01 (.36)	9.65 (.35)	41.17 (1.48)	40.00 (1.47)
$7000	11.34 (.38)	10.96 (.37)	45.32 (1.49)	43.24 (1.49)
$7500	12.94 (.40)	12.64 (.40)	50.72 (1.50)	47.39 (1.50)
$8000	14.56 (.42)	14.31 (.42)	54.95 (1.49)	51.62 (1.50)
$8500	16.47 (.44)	16.20 (.44)	59.46 (1.47)	56.44 (1.49)
$9000	18.36 (.47)	18.13 (.46)	63.51 (1.44)	61.17 (1.46)
$9500	20.46 (.48)	20.15 (.48)	68.11 (1.40)	66.04 (1.42)
$10000	22.68 (.50)	22.46 (.50)	71.53 (1.35)	70.81 (1.36)

Note: Because the number with earnings less than a given threshold is a binomial random variate, the standard error of the estimated percentage below that threshold (P) is computed as: sqrt[P(100-P)/N].



Graph 1-- Cumulative Distribution Functions of CPS Self-Reported Earnings (Y_{REP}) and of SSA Employer-Reported Earnings (Y_{TRUE}), Men.
(Proportions of Men with Self-Reported and with True Earnings
Below Each Earnings Threshold).



Graph 2-- Cumulative Distribution Functions of CPS Self-Reported Earnings (Y_{REP}) and of SSA Employer-Reported Earnings (Y_{TRUE}), Women.
(Proportions of Men with Self-Reported and with True Earnings Below Each Earnings Threshold).