MEASURING THE BIAS IN GROSS FLOWS IN THE PRESENCE OF AUTO-CORRELATED RESPONSE ERRORS

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I. INTRODUCTION

Frequently, a categorical variable will be observed at two or more points in time. The interior cells of the cross-classification of two observations are commonly referred to as gross flows or gross changes. Gross flow estimates are potentially of tremendous value in understanding processes. However, estimates are subject to very complex nonsampling errors that have discouraged their use.[1] In fact, the concept may be fundamentally unmeasureable in the sense that any attempt to measure gross flows may change the characteristics of the process.[2] The most serious problems usually present are mismatched observations, observations not missing at random, and misclassification in the observations. In this paper, we focus on misclassifications for dichotomous variables. To the best of our knowledge, prior work on the effect of misclassifications has assumed that misclassifications on the two observations are independent. We have developed a technique that takes advantage of the design of the Survey of Income and Program Participation (SIPP) to estimate the effect in the presence of auto-correlated errors. Even though not all requirements for the technique are currently met by SIPP design, we did try applying it. In Section II, we present a summary of the technique and the exploratory application. In Section III, we make recommendations for design changes in SIPP and indicate areas for future study. In Section IV, we discuss the technique in detail. In Section V, we present the application.

II. SUMMARY

Several features of the SIPP design are essential to the technique.[3] First, the reference period covers more than one point in time. (The SIPP reference period is four months for most variables.) Second, interviewing is staggered over several points in time (four months); i.e. one fourth of the sample is interviewed each month. Third, each person is interviewed repeatedly with each reference period immediately following the preceding period; i.e. there are no gaps. Taken together, these features tures imply that there are four measurements of the gross flows between any pair of consecutive months. (See Figure 1.)

Figure 1. Time in Sample by Rotation and Reference Month

Reference Month	Rotation 1	2	3	4
February	3	2	2	2
March	3	3	2	2
April	3	3	3	2
May	3	3	3	3
June	4	3	3	3
July	4	4	3	3

Example: Gross flows between April and May are observed from the third interview for rotations 1, 2, and 3. For rotation 4, they are observed by matching the second and third interviews.

Three of the measurements come from single interviews (the gross flows are within a single reference period), while one measurement comes from a pair of consecutive interviews. A final feature that is required but only partially satisfied is a reinterview program to supply corrected gross flows within reference periods. (While there is a SIPP reinterview program, it was not designed with this objective.)

The combination of error rates, dual within/between reference period measurements, corrected within period gross flows, and a few extra assumptions, would allow us to get a rough feeling for the correlation between measurement errors for consecutive months when the measurements are taken four months apart. If we could get that far, there is some reason to hope that the correlation would be similar for nonconsecutive months when measurements are taken four or more months apart. Given the error rates and the correlation, the bias in the gross flows would then be estimable.

This technique is admittedly weak. Only the intensity of interest in gross flows and the comparable weakness of known alternatives induced us to present it. Its greatest weakness is the requirement for a rigorous reinterview program to produce accurate reinterview data on gross flows within periods. Current survey reinterview programs are most effective at detecting curbstoning (interviewer fraud). Beyond that, they are notoriously unreliable.[4] Note, however, that we do not require the common assumption that the reinterview be independent of the original interview.[5] Nor do we require multiple reinterviews of the same respondent as has been recommended as a technique for dealing with correlated misclassifications.[6] (Field staff is generally strongly opposed to multiple reinterview contacts.) The alternative to reinterview data is administrative data. It is not clear whether the record-matching problems there will be much less severe than the problems with reinterview data. Besides, the number of variables for which administrative data exist is very limited.

Faced then with this dilemma, we decided to forge ahead, making whatever assumptions were required, in order to get some feeling for the magnitude of the bias in estimated gross flows from SIPP. We are, of course, aware that our estimates are extremely crude; we only hope that they will be viewed as being at least marginally useful in understanding a very difficult and pressing problem.

Due to the lack of reliable data including the reinterview data, we were forced to restrict the scope of our analysis to the characteristic of food stamps. Even that was in the form of a sensitivity analysis. Varying the parameters (error rates, etc.) used in the technique was necessary to assess the robustness of our results. Our analysis showed the results to be fairly robust. For almost all combinations of the parameter values, the bias in the gross flow estimates appears to be quite serious.

III. RECOMMENDATIONS AND FUTURE STUDY

We have demonstrated that the user of these estimates is taking a serious risk. Estimates of exit and entrance rates (defined in Section IV) might easily be substantially biased. It is thus clear that further and better research is urgently needed. We outline some avenues for future study below and welcome additional suggestions. Unfortunately, this research will take time. Meanwhile, data users require some guidance. Our only suggestion at this point is that users examine the ratios of month-to-month exit and entrance rates as observed between reference periods to those observed within reference periods. For those characteristics with large ratios, statements about gross flows over longer periods should be very tentative.

Perhaps we should focus more on how gross flows change over time than on the gross flows themselves. (This is done, for example, with CPS income estimates.) Note, however, that this requires stable instruments, procedures, and interviewing staff; so far, SIPP has changed a fair amount from panel to panel.

Areas for possible future study:

- Redesign reinterview program. Emphasize estimation of monthly error rates. Also, explore procedures other than simple repetition of original questions.
- Match SIPP into administrative databases. For some characteristics, obtain biases in gross flows directly. For others, obtain error rates for use in the technique proposed in this paper. Administrative data may also allow us to see if the relationship between true and observed gross flows depends on status at other points in time, such as, the time of interview or intervening time.
- Select special samples with known longitudinal characteristics from lists of program recipients, employees, taxpayers, etc.
- Subjectively examine gross flows to see if they "make sense."
- Explore reference periods of different lengths.
- Explore methods for increasing correlations between subsequent interviews such as conditioning response with a reminder of past response or longitudinal reconciliation.
- Explore the applicability of Colm O'Muircheartaigh's work on the correlation between interview and reinterview.

IV. DETAILED DESCRIPTION OF METHOD

Consider a Bernoulli variable observed at two points in time on one sample of a population. Assuming that the population is held constant, each unit can have one of four joint time statuses: (1,1), (1,0), (0,1), or (0,0). We will refer to these as flow types 1, 2, 3, and 4 respectively. Let $T=(T_1,\ldots,T_4)^T$ denote the population mean vector for the four gross flows. Let $Y=(Y_1,\ldots,Y_4)^T$ denote the vector of observed mean gross flows from the sample. We will assume that any under- coverage or nonresponse in the sample is ignorable and that the observations are perfectly matched. Thus the bias EY-T in the observed gross flows is due solely to misclassification. Let $m_{ij}=\Pr\{\text{unit of flow type } j \text{ is observed as flow type } i\}$ for $i=1,\ldots,4$ and $j=1,\ldots,4$. Let $M=((m_{ij}))$ be a 4x4 matrix. It is then easy to show that EY=MT. Our general idea is to estimate M and then estimate the bias as

$$\hat{\text{bias}} = Y-\hat{M}^{-1}Y = (I-\hat{M}^{-1})Y, \qquad (1)$$

where I is the 4x4 identity matrix.

Of course, estimating M is extremely difficult. Furthermore, there is evidence that M varies strongly by characteristic and by whether the gross flows are observed within a period or between periods.[7] It is also possible that M depends on status with respect to the characteristic of interest at another point in time, or other characteristics such as sex, region, income, etc. However, there is some reason to hope that M is fairly stable by characteristic for gross flows observed between periods but over varying time periods. This hope is based on heuristic arguments. If M does vary over time (between periods), it could be due to changing error rates or changing correlations between the errors. While the error rates do probably fluctuate from period to period, there is little reason to think that a trend would exist. As for the correlations, any correlation is probably due more to having the same poorly informed proxy respondent, the same poorly performing interviewer, or the same respondent misunderstanding of concepts, rather than active memory of response from the prior period. Thus while the correlations probably do weaken with increased time, the weakening may be rather slow. If the correlations do in fact weaken, our assumptions generally lead to an underestimate of the bias.

So we assume that an estimate of M for a pair of consecutive months observed between periods is still a reasonable estimate for a pair of months, for example, separated by 11 months. (A great deal of interest focuses on gross flows from a month to a year later.) Fortunately, estimating M for a pair of consecutive months is easier.

Let $C_1,\ldots,C_4$ be error rates for the four flow types at time 1 and $C_5,\ldots,C_8$ be error rates for the four flow types at time 2. (C_1 and C_2 are false negative rates at time 1 for flow groups 1 and 2. They are allowed to be different since we think that stable units may have a different rate than those actually experiencing a transition. The overall false negative rate at time 1 is $(T_1C_1+T_2C_2)/(T_1+T_2)$. C_3 and C_4 are false positive rates at time 1, C_5 and C_7 are false negative rates at time 2, and C_6 and C_8 are false positive rates at time 2.) Also, let $C_9,\ldots,C_{12}$ be the conditional probabilities of error at time 2 given error at time 1 for the four flow types. It is then fairly easy to show that

$$M = \begin{bmatrix} 1-C_1-C_5+C_1C_9 & C_6-C_2C_{10} & C_3(1-C_{11}) & C_4C_{12} \\ C_5-C_1C_9 & 1-C_2-C_6+C_2C_{10} & C_3C_{11} & C_4(1-C_{12}) \\ C_1(1-C_9) & C_2C_{10} & 1-C_3-C_7+C_3C_{11} & C_8-C_4C_{12} \\ C_1C_9 & C_2(1-C_{10}) & C_7-C_3C_{11} & 1-C_4-C_8+C_4C_{12} \end{bmatrix}$$

Using the reinterview, C_1 through C_8 may be directly estimated. Also, the reinterview provides an improved estimate Y_R of the gross flows. The problem is thus reduced to finding C_9 through C_{12} such that

$$MY_R = Y_B, \qquad (2)$$

where Y_B is the vector of observed gross flows between periods for the same pair of consecutive months. Unfortunately, the existence of a solution to (2) is quite rare.

We only sketch the proof of this assertion, leaving the details to the reader.

Letting $X = [1, -1, -1, 1]^T$, we may write M as $M = X[C_1C_9 \quad -C_2C_{10} \quad -C_3C_{11} \quad C_4C_{12}] + A$, where A does not depend on C_9 through C_{12}. Then (2) has a solution if, and only if, Y_B-AY_R is a multiple of X. While least square solutions do exist, there is no unique solution. (Any $(C_9,\dots,C_{12})$ such that $(M-A)Y_R$ is the projection of Y_B-AY_R onto X is a least squares solution.)

Thinking this over, we realized that we had insufficient data to estimate the error correlation for each flow type separately. Somehow, it was necessary to define a measure of association that would apply simultaneously to the four flow types. We came up with the idea that $(C_9,\dots,C_{12})^T$ should lie on the line between the points $(1,0,0,1)^T$ and $(C_5,\dots,C_8)^T$. We then defined the measure of association r to be the ratio of the Euclidean distance between $(C_9,\dots,C_{12})^T$ and $(C_5,\dots,C_8)^T$ to that between $(1,0,0,1)^T$ and $(C_5,\dots,C_8)^T$. This has some intuitive appeal since if r=0, then $(C_9,\dots,C_{12})^T = (C_5,\dots,C_8)^T$, which implies that errors occur independently. On the other hand, if r=1, then $(C_9,\dots,C_{12})^T = (1,0,0,1)^T$, which implies strong dependence on errors. For example, it implies all correlation of 1.0 among flow types 1 and 4 (the no change categories) provided that the error rates are equal at time 1 and time 2. In addition, it implies a strong negative correlation among flow types 2 and 3 (the with change categories). Another way of conceptualizing r=1 is: if an error is made at the first observation, then the same response will be obtained at the second observation regardless of the flow type of the unit. With some algebra, we obtain the value of r that minimizes $\|MY_R-Y_B\|^2$:

$$r = \frac{X^T(Y_B-AY_R) - 4\left(C_1C_5 \quad -C_2C_6 \quad -C_3C_7 \quad C_4C_8\right)Y_R}{4\left(C_1(1-C_5) \quad C_2C_6 \quad C_3C_7 \quad C_4(1-C_8)\right)Y_R} \qquad (3)$$

To summarize, our technique is to estimate C_1 through C_8 and Y_R from reinterview, then use these with Y_B to estimate r. Using r and linear interpolation, we can estimate C_9 through C_{12}. We can then compute an estimate of M, and apply $(I-\hat{M}^{-1})$ to any observed gross flows between periods to estimate the biases in the gross flows.

This technique also provides estimates of bias in transition rates, the percentages of those with an initial status who change status by the second time point. Let the elements of $\hat{M}^{-1}Y$ be denoted Z_1 through Z_4. Then the biases in the transition rates are

$$\frac{Y_2}{Y_1+Y_2} - \frac{Z_2}{Z_1+Z_2} \quad \text{and} \qquad (4)$$

$$\frac{Y_3}{Y_3+Y_4} - \frac{Z_3}{Z_3+Z_4} \quad . \qquad (5)$$

(4) and (5) are referred to as the bias in the exit and entrance rates, respectively.

V. SENSITIVITY ANALYSIS

Given the uncertainties in the estimation of the error rates and the improved estimate of gross flows discussed in Section II, we believed an appropriate approach to getting an idea of the magnitude of the bias in gross flow estimates from SIPP was to perform sensitivity analysis.

Due to the weakness of the data produced from the SIPP reinterview, we limited our analysis to the gross flow estimates of food stamp program participation. In particular, the unit of analysis was the authorized person of a food stamp unit. (A food stamp unit is all persons covered under an authorized person's allotment.) We focused on food stamps because their error rates seemed more plausible than those of other characteristics. The main reasons for presenting this analysis of food stamp gross flows are to provide some information on the probable magnitude of biases in gross flow estimates from SIPP and to illustrate the application of the technique. Another reason is to observe how sensitive the biases in gross flow estimates are to changes in the error rates, Y_R, and the year-to-year gross flow estimates. The greater the sensitivity, the less reliable the comparisons of gross flows across demographic groups or across time will be if we do not maintain a high degree of uniformity in SIPP data collection and processing procedures.

Our sensitivity analysis consists of varying the estimate of M for food stamps by varying the values of C_1 through C_8 and Y_R.

We then estimate biases by applying $(I-\hat{M}^{-1})$ to observed food stamp gross flows between periods and evaluate the sensitivity of these biases to the changes in C_1 through C_8 and Y_R. For this analysis, we studied observed <u>year-to-year</u> food stamp gross flows because of interest expressed in the production of statistics based on year-to-year gross flow estimates from SIPP. As an additional part of our sensitivity analysis, we varied the year-to-year gross flow estimates. The purpose was to study the reliability of comparisons of gross flow estimates across demographic groups or across time.

In our presentation of the sensitivity analysis of the bias in gross flow estimates for food stamps, we first describe the estimation of parameters needed to apply the technique. We then discuss how these parameters were varied to perform the sensitivity analysis. Finally, we present the results.

A. Estimation of Parameters for Food Stamps

Error rates, an improved estimate of consecutive month-to-month gross flows, and observed gross flows must be estimated to apply the technique. Observed food stamp gross flow estimates are readily available from SIPP data. However, the estimation of error rates and improved gross flow estimates for food stamps are much more subjective. The methodology used to estimate these parameters is discussed below.

1. Error Rates

Several assumptions are required in order to determine the error rates $(C_1,\dots,C_8)$ from the SIPP reinterview. The SIPP reinterview references the entire period--not each month within the period. Thus, we are unable to differentiate time 1 and time 2 error rates based on length of recall. In addition, we are unable to differentiate error rates, for a specific time, based on the flow type. These two limitations forced us to assume $C_1 = C_2 = C_5 = C_7$ and $C_3 = C_4 = C_6 = C_8$. Therefore, the determination of the error rates is reduced to computing two error rates: the probability of falsely observing no food stamps (false negative) and the probability of falsely observing food stamps (false positive).

These error rates were actually computed for food stamps and several other characteristics from the SIPP reinterview. Upon examination of these error rates we immediately questioned their surprisingly small magnitude. We realized that error rates referencing the entire period would most likely be smaller than those that reference a single month, which we would have preferred. To estimate the magnitude of this underestimate we examined AFDC (Aid to Families with Dependent Children) data from ISDP (Income Survey Development Program).[8] The data indicated that the false negative error rate computed from administrative record checks was approximately three times larger than that computed from the SIPP reinterview. (False positive error rates were unavailable.) Believing the ISDP error rates to be more realistic, we applied a factor of 3 to the food stamp false negative error rate.

In considering the computation of the false positive error rate for food stamps, we realized that the false positive observations were in terms of food stamp units while the true negative observations were in terms of persons 18 and over. To adjust for this we applied a factor of 1.4 (average number of persons 18 and over in a food stamp unit) to the false positive error rate.

Thus, the above assumptions and adjustments provide us with the following estimates of the error rates:

False Negative = $C_1 = C_2 = C_5 = C_7 = 0.0597$

False Positive = $C_3 = C_4 = C_6 = C_8 = 0.0034$

2. Improved Estimate of Gross Flow for Food Stamps

Our intuition tells us that flow types 2 and 3 (the with change categories) are probably overestimated and underestimated by gross flows observed between and within periods, respectively. However, we thought we had a better understanding of the nature of the underestimates in flow types 2 and 3 observed within a period. We intuited that within a period flow types 2 and 3 may be observed as flow types 1 and 4, while flow types 1 and 4 are not as likely to be observed as flow types 2 and 3. This corresponds to r=1 with the error rates for flow types 1 and 4 equal at time 1 and time 2. Thus, an improved estimate of consecutive month-to-month gross flows for food stamps is computed as follows:

$$Y_R = \hat{M}^{-1}_{r=1} Y_W,$$

where Y_W is the vector of observed gross flows within a period. For food stamps, $Y_W = [.039867\ .001287\ .001645\ .957202]^T$ which results in an improved estimate of consecutive month-to-month gross flows $Y_R = [.038923\ .001374\ .001756\ .957948]^T$

B. Varying the Parameters for Food Stamps

Given the subjective nature of the estimation of C_1 through C_8 and Y_R we thought it necessary to study the robustness of the estimated biases to assess their usefulness. To accomplish this we arbitrarily decreased and increased the error rates. We also used different improved estimates, Y_R. One Y_R was a weighted average of the observed gross flows within and between periods. Another Y_R was somewhat arbitrarily computed, so as to have gross flows with change that were closer to the gross flows with change from between periods.

C. Results

It is our understanding that of central interest in the problem of biases in gross flow estimates is the production of transition rates (defined in Section IV). Consequently, our sensitivity analysis results are presented in terms of the biases in the transition rates.

To assess the seriousness of the magnitude of the bias in a transition rate, we compared it to an estimate of the standard error of the transition rate. The greater the absolute value of the ratio of bias to standard error is; the more serious the problem.

Using the observed year-to-year gross flows for food stamps we computed the ratio of bias to standard error of the transition rates for several combinations of error rates and Y_R (Table A).

The rows of Table A are the various error rates used. The first row (original) is the error rates estimated in Section V.A.1. Still concerned about the possible underestimation of the error rates, we used the remaining permutations of doubling the false negative and false positive error rates in rows two through four. Concerned with the assumption that, error rates are the same for all flow types, in particular, the with change categories versus the without change categories, we doubled the error rates for flow types 2 and 3 (the with change categories) in the fifth row. In the opposite direction of the top five rows, we used the unadjusted false negative error rate in the sixth row. (See Figure 2.)

Figure 2. Error Rates by Type of Error and Row

Row	False Negative ($C_1=C_2=C_5=C_7$)	False Positive ($C_3=C_4=C_6=C_8$)
1	.0597	.0034
2	.1194	.0034
3	.0597	.0068
4	.1194	.0068
5	$C_1=C_5=.0597, C_2=C_7=.1194$	$C_3=C_6=.0068, C_4=C_8=.0034$
6	.0199	.0034

The columns of Table A are the three values for Y_R. The first column is our intuited estimate of Y_R, as explained in Section V.A.2. Flow types 2 and 3 of our intuited Y_R are very close to those of the observed gross flows within a period Y_W. The middle column is a weighted average of Y_W (three fourths weight) and the observed gross flows between periods Y_B (one fourth weight), where $Y_B = [.036444\ .005865\ .004461\ .953229]^T$ for food stamps. For the weighted average Y_R, flow types 2 and 3 are larger, but still closer to those of Y_W. Note, respectively, these two columns correspond to month-to-month over-reporting and equivalent-reporting of flow types 2 and 3. The last column corresponds to the other extreme of month-to-month under-reporting of flow types 2 and 3. For this column, flow types 2 and 3 are about in the middle of those for Y_W and Y_B. (See Figure 3.)

Figure 3.Gross Flows by Assumed Y_R and Flow Type

Flow Type	Intuition	Weighted Average	Upper Estimate
1	.038923	.039011	.037954
2	.001374	.002431	.003488
3	.001756	.002349	.002942
4	.957948	.956209	.955616

For each combination of error rate and Y_R in Table A, we computed the ratio of bias to standard error for exit (upper right) and entrance (lower left) rates. For example, the ratios for exits and entrances are 5.13 and 4.85, respectively, for the original error rates and the intuited Y_R (extreme upper left cell). (Detailed results along with a more detailed explanation of the application of the technique to compute these ratios are provided in Appendix A.) The reported year-to-year exit rate is 29.54%. Referring to Table A-11 in Appendix A, the technique estimated the "true" year-to-year exit rate to be 23.23% with a standard error (SE) of 1.23%. This results in a bias to SE ratio of 5.13 ((29.54%-23.23%)/1.23%) for exits. Similarly for entrances, the bias to SE ratio is 4.85 ((.978%-.667%)/.064%).

The implications of the magnitude of these ratios are evident. For most applications, a ratio less than .75 is not serious, while a ratio greater than 1.5 is cause for some concern.

However, as stated earlier, to assess the robustness of this result, we varied the error rates and Y_R. The results of each combination constitute the remainder of Table A.

In the first column, varying the error rates does affect the ratios to some extent. Still, the magnitude of the ratios is large, even when all the error rates are doubled (row 4): exit ratio=3.26 and entrance ratio=4.07. In the second column (Y_R=Weighted Average) the ratios are smaller than the corresponding ratios in the first column, but all are still large enough for concern. Even for the extreme assumption of Y_R in the third column, the ratios are large except for the exit ratio when the false negative error rate is doubled (Rows 3 and 4). So, for almost every combination of error rate and Y_R in Table A, the magnitude of the bias in the observed year-to-year transition rates relative to the standard error appears to be quite serious.

Another part of our sensitivity analysis was to assess the effect of varying the observed year-to-year gross flow estimates. To accomplish this, we decreased and increased flow types 2 and 3 by 30%. (Note, the sum of flow types 1 and 2 and the sum of flow types 3 and 4 were held constant.) Table B contains the results of the 30% decrease in flow types 2 and 3. (Detailed results are given in Appendix B.) Compared to Table A, all the ratios appear to have increased by at least 50%. Clearly, with these exit and entrance rates, the magnitude of the bias relative to the standard error is very serious for all combinations of error rates and Y_R. Table C contains the results of the 30% increase in flow types 2 and 3. (Detailed results are given in Appendix C.) Comparison of ratios to Table A vary by the assumed Y_R. For columns 1 and 2 of Table C, almost all of the ratios (except exit ratios for rows 3 and 4) decreased by about 30%, but are still greater than 1. However, in column 3, the absolute value of almost all of the ratios is at the most 1.5, with the smaller ratios coming from the rows with doubled error rates. This means that the magnitude of the bias relative to the standard error is generally not as serious for these certain combinations of increased error rates, Y_R, and year-to-year gross flow estimates. However, these combinations are rather extreme compared to our original combination of error rates, intuited Y_R and observed year-to-year gross flow estimates.

D. Summarization of Results

For the characteristic of food stamps, the ratio of bias to standard error was sensitive to the assumption of Y_R and the year-to-year gross flow estimates and, to a lesser extent, the error rates. The combinations of these variables covered a very large part of the realm of reasonable possibilities. In almost all cases, the magnitude of the ratio indicated a serious bias in observed transition rates. Yet, there were sufficient changes in the ratio to warrant concern about the reliability of comparisons between transition rates if a high degree of uniformity in SIPP data collection and processing procedures is not maintained.

FOOTNOTES

[1] For an excellent overview of the history of the problem, see the proceedings of the recent conference [8].

[2] Parnes [2] first formulated a type of uncertainty principle in this area. A good example is participation in government programs. Respondents may learn of these at the first contact and avail themselves of the benefit by the second contact.

[3] For an overview of SIPP, see [7].

[4] A general description of reinterview as conducted at the Bureau is given in [3]. An internal critique is given in [4]. The results of an experiment with independent reconciliation are given in [5]. Design modifications are given in [6].

[5] See, for example, Fuller and Chua in [8] pp. 65-77.

[6] Recommendation number 3 on page 135 of [8].

[7] See [1] for a comparison of within a period and between period gross flows.

[8] For a more detailed discussion of AFDC error rates in ISDP, see [9].

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TABLE A

Ratio of Bias to Standard Error for Observed Year-to-Year Transition Rates for Food Stamps

		Assumed True Month-to-Month Gross Flows (Y_R)		
		Intuition (Near Within) (1)	Weighted Average (2)	Upper Estimate (Near Between) (3)
ERROR RATES	Original (1)	5.13 4.85	3.46 3.38	1.95 2.14
	Double False Negative (2)	5.33 4.15	3.71 2.73	1.55 2.30
	Double False Positive (3)	3.26 4.94	1.55 3.47	-0.04 2.20
	Double All (4)	3.26 4.07	1.67 2.70	0.23 1.54
	Double Both for Flow Types 2 & 3 (5)	4.22 4.16	2.64 2.76	1.22 1.57
	One Third of False Negative (6)	5.33 5.59	3.54 4.00	1.89 2.63

Key

	Y_R
ERROR RATE	Ratio for Exits Ratio for Entrances

Year-to-Year Gross Flow for Food Stamps = [2.90% 1.21% 0.94% 94.95%]

Exit Rate for Food Stamps = 29.54% Standard Error = 1.23%

Entrance Rate for Food Stamps = 0.978% Standard Error = 0.064%

TABLE B

Ratio of Bias to Standard Error for Decreased Observed Year-to-Year Transition Rates for Food Stamps

		Assumed True Month-to-Month Gross Flows (Y_R)		
		Intuition (Near Within) (1)	Weighted Average (2)	Upper Estimate (Near Between) (3)
ERROR RATES	Original (1)	7.67 7.64	5.27 5.16	3.26 3.27
	Double False Negative (2)	8.23 7.50	5.82 4.95	3.85 3.08
	Double False Positive (3)	6.05 7.59	3.70 5.17	1.66 3.28
	Double All (4)	6.28 7.08	4.02 4.74	2.10 2.94
	Double Both, for Flow Types 2 & 3 (5)	6.98 7.23	4.70 4.83	2.79 3.00
	One Third of False Negative (6)	7.66 8.12	5.18 5.54	3.04 3.54

Key

	Y_R
ERROR RATE	Ratio for Exits Ratio for Entrances

Year-to-Year Gross Flow for Food Stamps = [3.26% 0.85% 0.66% 95.23%]

Exit Rate for Food Stamps = 20.68% Standard Error = 0.98%

Entrance Rate for Food Stamps = 0.685% Standard Error = 0.046%

TABLE C

Ratio of Bias to Standard Error for Increased of Observed Year-to-Year Transition Rates for Food Stamps

		Assumed True Month-to-Month Gross Flows (Y_R)		
		Intuition (Near Within) (1)	Weighted Average (2)	Upper Estimate (Near Between) (3)
ERROR RATES	Original (1)	3.70 3.49	2.33 2.41	1.05 1.46
	Double False Negative (2)	3.70 2.50	2.42 1.49	1.26 0.62
	Double False Positive (3)	1.48 3.66	0.01 2.55	-1.39 1.56
	Double All (4)	1.34 2.56	0.01 1.56	-1.24 0.67
	Double Both for Flow Types 2 & 3 (5)	2.66 2.62	1.36 1.60	0.16 0.70
	One Third of False Negative (6)	4.04 4.40	2.53 3.20	1.09 2.11

Key

	Y_R
ERROR RATE	Ratio for Exits Ratio for Entrances

Year-to-Year Gross Flow for Food Stamps = [2.53% 1.58% 1.22% 94.67%]

Exit Rate for Food Stamps = 38.40% Standard Error = 1.37%

Entrance Rate for Food Stamps = 1.272% Standard Error = 0.078%