Econometrica, Vol. 54, No. 6 (November, 1986), 1319-1338

REPORTING ERRORS AND LABOR MARKET DYNAMICS

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This paper estimates the incidence of response errors in the Current Population Survey. It proposes a procedure for adjusting the Bureau of Labor Statistics' gross flows data on labor market transitions to account for these errors. Although the findings are not definitive because the procedure makes particular assumptions regarding the stochastic process generating response errors, they illustrate the potentially substantial effect of response errors on studies of labor market behavior. The adjustment procedure suggests that because measurement errors give rise to spurious transitions between labor market states, the labor market may be less dynamic than previously thought. The results imply that conventional measures may understate the duration of unemployment by as much as eighty per cent, and overstate the frequency of labor force entry and exit by even more.

KEYWORDS: Labor markets, unemployment, Current Population Survey, response error models, survey data.

THE DYNAMICS OF the American labor market have been an important focus of research over the last decade. Early work by Hall (1972), Feldstein (1973), and Marston (1976) suggested that most unemployment was due to normal turnover, not to individuals with special employment problems. A typical conclusion was that of Feldstein (1973) who wrote that "almost everyone who is out of work can find his usual job in a relatively short time" (p. 11). This dynamic view of unemployment has been challenged in the more recent work of Clark and Summers (1979a) and Akerlof and Main (1980). Clark and Summers in particular focus on how analysts can be misled by spurious labor market transitions, writing that "it seems likely that some of the observed flows into and out of the labor force arise from inconsistent reporting of consistent behavior" (p. 28). This paper re-examines the empirical basis of this debate.

Studies of labor market dynamics are of necessity based on survey data. In some cases inferences are drawn from individual responses to retrospective questions. In other cases, presumably more accurate inferences are drawn from panel data in which individuals are interviewed several times. The Bureau of Labor Statistics gross changes data, which have been tabulated since 1948, are a major source of information about individuals' labor market experience. While the data have not been published in recent years due to concerns about accuracy, they have been used in numerous studies of labor market dynamics.[2]

[1] We are indebted to Bruce Meyer for outstanding research assistance and many helpful discussions, to Irv Shreiner and Paul Flaim for data assistance, and to Wayne Fuller, Francis Horvath, two anonymous referees, and Angus Deaton for helpful suggestions. A preliminary version of this paper was presented at the BLS/Census Conference on Gross Changes Data, July, 1984. After completing most of the research reported here, we learned of related work by Fuller and Chua (1983, 1985) and Abowd and Zellner (1985a, b). We thank the NBER and NSF for financial support. This research is part of the NBER Program in Labor Studies.

[2] Clark and Summers (1979a), Smith and Vanski (1979a), and Smith (1973), among others, have used unpublished gross flows data to examine labor market dynamics.

The report of the National Commission on Employment and Unemployment Statistics (1979) recommended that despite the data difficulties, the BLS should resume publication of the gross changes data on an occasional basis. Moreover, the Commission noted that "the importance of Current Population Survey based gross changes data for enhancing understanding of changes in the labor market requires that very high priority be given to improvement in the data. . . . It is possible, of course, that a solution will not be achieved, but the potential value of the data warrants an intensive effort" (p. 217).

The flows of individuals between different labor market states are derived from longitudinal data by comparing the responses of individuals on two different survey dates. On each survey, some individuals are incorrectly classified with respect to labor market status. While these errors may largely cancel in tabulations of the unemployment rate or other labor market aggregates, estimated flow rates between labor market states may be extremely sensitive to them. Individuals who are misclassified in one month but not in the next are reported as moving from one state to another even though their behavior has not changed. Some observed transitions are therefore spurious. This may lead to substantial overestimation of the amount of labor market mobility, and impart significant biases to estimates of the expected duration of both unemployment and nonparticipation spells. Response errors may also contaminate inferences about subtler aspects of labor market dynamics, such as differences between demographic groups or the presence of "state dependence" effects.

This paper presents a technique for correcting the classification errors which plague the Current Population Survey (CPS) gross changes data. Similar techniques may be applicable to other data sets. We use the CPS Reinterview Survey to estimate the incidence of errors in the gross changes data, and then calculate revised labor market flows by adjusting for spurious transitions. Although our findings are not definitive because we make particular assumptions about the stochastic process generating response errors, the results suggest that conventional measures may greatly overstate flows into and out of the labor force. As a consequence, standard estimates of unemployment durations, whether based directly on gross flows data or on other information such as the average duration of completed or incomplete spells, may display substantial downward biases. The labor force attachment of some groups, notably women and teenagers, may also have been significantly underestimated.

This paper is divided into five sections. The first explains our procedure for estimating the incidence of response errors in the CPS and documents that the error rates for a single month are in some cases comparable to transition rates observed from month to month. Section 2 presents our algorithm for adjusting the gross changes data, and contrasts our revised labor market flows with the unadjusted data. It also examines the precision of our estimated adjustments. The next section explores the robustness of our findings to some of our method's maintained assumptions. Section 4 uses the adjusted flows to analyze several characteristics of the American labor market, focusing on the experience of different demographic groups. The concluding section suggests directions for future work.

1. CLASSIFICATION ERRORS AND THE CURRENT POPULATION SURVEY

Our objective is to estimate the true transition rates between the labor market states of employment (E), unemployment (U), and not-in-the-labor force (N). This information is conveniently represented by a transition matrix:

$$(1) \qquad P = \begin{bmatrix} p_{EE} & p_{EU} & p_{EN} \\ p_{UE} & p_{UU} & p_{UN} \\ p_{NE} & p_{NU} & p_{NN} \end{bmatrix}$$

where, for example, p_{EU} is the probability than an individual who is employed in month t is unemployed in month $t+1$. Data on the transition matrix P may be derived from the monthly CPS since three quarters of the sample in a given month is included again in the next month.[3] The top panel of Table I provides average values of P for the 1977-1982 period.

There are strong reasons to believe that these raw data substantially overstate the true amount of turnover in the labor market. Taken literally, they imply that there are over fifty million labor force entrances each year, which seems implausible. Additional evidence is provided by information on CPS error rates which is generated as a byproduct of the CPS Reinterview Survey.[4] In the Reinterview Survey, which is used primarily for survey quality control, individuals are contacted about one week after their initial interview and asked once again about their labor market status in the original survey week. Except for errors, the Initial and Reinterview Survey results should coincide. The lower half of Table I presents "transition" rates calculated by comparing the Initial and Reinterview Surveys.

TABLE I

ACTUAL AND SPURIOUS TRANSITIONS IN THE CURRENT POPULATION SURVEY[a]

A. Transition Probabilities from Two Consecutive Monthly Interviews

Initial Month Labor Market Status	Subsequent Month Labor Market Status: Employed	Unemployed	NILF
Employed	.950	.017	.033
Unemployed	.255	.536	.209
NILF	.047	.027	.926

B. Implied Transition Probabilities from Interview and Reinterview Surveys

Initial Interview Labor Market Status	Reinterview Labor Market Status: Employed	Unemployed	NILF
Employed	.965	.010	.026
Unemployed	.097	.742	.161
NILF	.038	.023	.940

[a] Each entry shows the probability of transiting conditional upon initial labor market status. Panel A is based on the average values of the unpublished gross changes data for all demographic groups for the years 1977-1982. Panel B is based on the authors' data set of all Unreconciled Reinterview Surveys conducted between January and June, 1981.

[3] For a discussion of the gross changes data, see Smith and Vanski (1979b).

[4] The CPS Reinterview Survey is described in some detail in Census Technical Report # 19 (1969), Woltman and Schreiner (1979), and Graham (1979).

It is apparent that these transition rates between different states, which are *all spurious*, are very large relative to observed month to month transition rates. For example, the rate of labor force withdrawal from unemployment is 20.1 per cent in the longitudinal data but appears to be 16.1 per cent in the comparison between the Initial and Reinterview Surveys.

This paper combines error rate information from the Reinterview Survey with observed month to month transition rates to estimate true transition rates. Our first step is to calculate a matrix of response error rates showing the probability that an individual whose *true* labor market status is i ($S_T = i$) will be classified as in state j in an initial CPS interview ($S_1 = j$). We define $q_{ij} = \Pr(S_1 = j \mid S_T = i)$. The matrix of error rates is

$$Q = \begin{bmatrix} q_{EE} & q_{EU} & q_{EN} \\ q_{UE} & q_{UU} & q_{UN} \\ q_{NE} & q_{NU} & q_{NN} \end{bmatrix} \tag{2}$$

where, for example, q_{EN} is the probability that an individual who is employed will be measured as not-in-the-labor force. There are only six independent probabilities in this matrix, since the elements of each row sum to unity.

The Reinterview Survey includes 5.6 per cent of the CPS respondents in each month. Households which are included in the Reinterview Survey are divided into a Reconciled and an Unreconciled Subsample, accounting for eighty and twenty per cent of the reinterviews respectively. The allocation of households to subsamples is made prior to the Reinterview Survey. For households in the Reconciled Subsample, the reinterviewer has access to the original survey responses. He conducts a second interview, compares the results with those on the first survey, and then attempts to determine which, if either, of any conflicting responses is correct. The results of this reconciliation are recorded on a third form and tabulated along with the Initial Interview and Reinterview Survey responses. For the twenty per cent of the Reinterview Survey respondents in the Unreconciled Subsample, the reinterviewer is denied access to the Initial Interview data. He conducts a second interview and makes no attempt to compare responses with those on the Initial Interview.

The Bureau of the Census tabulates Reinterview Survey results for some highly aggregated demographic groups. To investigate differences in labor market experience for different demographic groups, we made our own tabulations of error rates from data tapes provided by the Census Bureau. Table II shows the distribution of recorded labor market status for individuals in the Reconciled and Unreconciled Subsamples of our data set, which contains 25,314 reinterviews conducted between January and June, 1981. Off-diagonal elements correspond to different responses on the two surveys. The table suggests a significant amount of response error in the CPS. More than five per cent of the individuals in the Unreconciled Subsample were classified differently on the two surveys.

The data in Table II exhibit an important anomaly. The incidence of discrepancies between the Initial and Reinterview Surveys is much greater in the Unreconciled than in the Reconciled Sample. This finding, which has been reported by

TABLE II

SURVEY RESPONSE INCONSISTENCIES, CPS REINTERVIEW SURVEY[a]

Reconciled Subsample: Initial Interview vs. Reinterview

Initial Interview Status	Reinterview Status Employed	Unemployed	NILF
Employed	57.69	0.17	0.71
Unemployed	0.18	4.02	0.34
NILF	0.90	0.66	35.34

Unreconciled Subsample: Initial Interview vs. Reinterview

Initial Interview Status	Reinterview Status Employed	Unemployed	NILF
Employed	57.65	0.59	1.53
Unemployed	0.43	3.28	0.71
NILF	1.35	0.82	33.64

[a] Each entry represents the percentage of individuals recorded in a particular pair of labor market states. For example, 57.69 per cent of the individuals in the Reconciled Subsample were recorded as employed in both the Interview and the Reinterview Surveys. Calculations are based on the authors' tabulations of Current Population Survey Reinterviews for the period January through June, 1981.

others using data for different years, may indicate that the procedures specified for reinterviewers are not carried out.[5] Some reinterviewers, when provided with copies of the household's original survey responses for reconciliation purposes, may use them as a guide in completing the Reinterview Survey. This reduces their workload by minimizing the need for reconciliation.

This anomaly complicates the estimation of error rates. We want to use the Reconciled Subsample information on "true labor force status" but at the same time use the Unreconciled Subsample to estimate the actual incidence of error.[6] We therefore proceed as follows. For individuals in the Reconciled Subsample, we estimate the probability of truly being in each labor market state conditional upon reported first and second interview status (S_1 and S_2). These probabilities are:

$$w_{ijk} = \Pr(S_T = k \mid S_1 = i, S_2 = j). \tag{3a}$$

To estimate these probabilities, we assume that when there are inconsistencies between the two survey responses, the reconciliation procedure correctly identifies true labor market status. When the two surveys agree, we follow the BLS reconciliation procedure and assume that they are correct ($S_R = S_1 = S_2$). Our estimator is therefore:

$$\hat{w}_{ijk} = \Pr(S_R = k \mid S_1 = i, S_2 = j). \tag{3b}$$

[5] Discussion of the bias induced by the reconciliation procedure may be found in Schreiner (1980).

[6] Abowd and Zellner (1985a, b) present an adjustment procedure for the gross changes data which relies only on the Reconciled Subsample data, while Fuller and Chua (1983, 1985) rely only on the Unreconciled Subsample.

The twenty-seven probabilities defined by (3b) must satisfy nine adding-up conditions of the form

$$w_{ijE} + w_{ijU} + w_{ijN} = 1 \qquad (i = E, U, N; j = E, U, N). \tag{4}$$

Therefore, only eighteen of the twenty-seven w_{ijk} parameters are independent.

We assume that the Reconciled Subsample contains a partial sample of the cases for which Initial Interview and Reinterview responses are different. Although the Reconciled Subsample provides a misleading estimate of the incidence of response errors, it may nonetheless provide reliable estimates of the fraction of inconsistent cases which should be allocated to each of the two recorded responses.

We use the estimates $\{\hat{w}_{ijk}\}$ to impute a probability distribution of true labor market status for each individual in the Unreconciled Subsample, conditional upon his recorded responses in the Initial Interview and the Reinterview. The number of individuals in the Unreconciled Subsample with each imputed labor market status is:

$$\hat{N}_k^U = \text{Number of individuals in the Unreconciled Subsample with imputed labor market status } k = \sum_i \sum_j \hat{w}_{ijk} N_{ij}^U. \tag{5}$$

N_{ij}^U is the number of individuals in the Unreconciled Subsample with Initial Interview status i and Reinterview status j. From these estimates we calculate the probability that an individual observed in a particular labor market state on either the first or second survey is actually in state k. The probability that an individuals' recorded Initial Interview response is y, conditional upon our imputed reconciliation status being x, is

$$\hat{q}'_{xy} = \frac{\sum_j \hat{w}_{yjx} \cdot N_{yj}^U}{\hat{N}_x^U} = \frac{\sum_j \hat{w}_{yjx} \cdot N_{yj}^U}{\sum_i \sum_j \hat{w}_{ijx} \cdot N_{ij}^U} = \Pr(S_1 = y \mid \hat{S}_T = x) \tag{6a}$$

where $\hat{S}_T$ denotes our imputed labor market status. An identical procedure using the Reinterview Survey (S_2) as the observed response yields:

$$\hat{q}''_{xy} = \frac{\sum_j \hat{w}_{jyx} \cdot N_{jy}^U}{\hat{N}_x^U} = \frac{\sum_j \hat{w}_{jyx} \cdot N_{jy}^U}{\sum_i \sum_j w_{ijx} \cdot N_{ij}^U} = \Pr(S_2 = y \mid \hat{S}_T = x). \tag{6b}$$

We form the estimated error rates which are used in our subsequent analysis by averaging $\hat{q}'_{xy}$ and $\hat{q}''_{xy}$: $\hat{q}^*_{xy} = (\hat{q}'_{xy} + \hat{q}''_{xy})/2$. Since $\hat{q}'_{xy} \cong \hat{q}''_{xy}$, the last step is of little significance.

Our estimates of classification error probabilities, and their associated standard errors, are shown in Table III. Only off-diagonal elements of the Q matrix are

TABLE III
ESTIMATED RESPONSE ERRORS IN THE CURRENT POPULATION SURVEY[a]

	Sample Size	q_{EU}	q_{EN}	q_{UE}	q_{UN}	q_{NE}	q_{NU}
Total	25,314	.0054	.0172	.0378	.1146	.0116	.0064
		(.0007)	(.0018)	(.0070)	(.0109)	(.0013)	(.0009)
Men 16–19	1,220	.0168	.0350	.0644	.1134	.0120	.0143
		(.0085)	(.0119)	(.0300)	(.0358)	(.0072)	(.0075)
Men 20–24	1,399	.0137	.0077	.0550	.0728	.0170	.0378
		(.0054)	(.0039)	(.0302)	(.0280)	(.0151)	(.0196)
Men 25–59	6,812	.0046	.0062	.0316	.0700	.0378	.0332
		(.0013)	(.0016)	(.0136)	(.0207)	(.0134)	(.0127)
Women 16–19	1,281	.0088	.0380	.0222	.1736	.0130	.0114
		(.0062)	(.0118)	(.0182)	(.0454)	(.0060)	(.0055)
Women 20–24	1,538	.0096	.0218	.0234	.1011	.0239	.0105
		(.0051)	(.0067)	(.0254)	(.0391)	(.0102)	(.0065)
Women 25–59	7,711	.0029	.0168	.0380	.1688	.0106	.0062
		(.0011)	(.0025)	(.0164)	(.0254)	(.0022)	(.0020)
Both Sexes, 16–19	2,501	.0126	.0361	.0472	.1393	.0131	.0126
		(.0051)	(.0074)	(.0199)	(.0309)	(.0044)	(.0042)

[a] Error rates are calculated from the authors' data set of Reinterview Surveys for the period January through June, 1981. Values in parentheses are standard errors.

shown, since the diagonal terms can be computed from them. The table displays separate error rates for the entire population and seven demographic subgroups. The standard errors are calculated using a "bootstrap" procedure of the type described in Efron (1982).[7] The error rates for the larger population subgroups can be estimated quite precisely, but the estimated error rates for the smaller groups are sometimes subject to substantial uncertainty.

The error rates are highest for unemployed individuals. In the whole survey, over eleven per cent of the unemployed are incorrectly classified as not in the labor force. The fraction of unemployed persons misclassified in this way varies across demographic groups, from less than seven per cent for men aged 25–59 to over seventeen per cent for women aged 16–19. For teenagers of both sexes, the error rate is nearly fourteen per cent. At all ages, the error rate is substantially higher for women than for men.

Misclassification from unemployment into employment is also important. Almost four per cent of the unemployed individuals in the population are incorrectly classified as holding a job; this error rate rises to over six per cent for male teenagers. Errors in which employed individuals are classified as not-in-the-labor force are also surprisingly frequent. Nearly two per cent of the employed, and three and a half per cent of employed teenagers, are miscategorized in this

[7] The empirical frequency distributions from both the Reconciled and Unreconciled Subsamples, which form the basis for our estimates of the w_{ijk} and the N_{ij}^{U}, are used in calculating bootstrap standard errors. We generate 1000 synthetic data sets by drawing randomly from these empirical frequency distributions. For each sample we then carry through the calculations of the q_{ij}^{*}. Our reported standard errors are the standard deviations of the 1000 synthetic estimates of q_{ij}^{*}. We also calculated confidence bands using the .025 and .975 percentile values of the synthetic estimates, but these proved very close to the confidence intervals implied by our standard deviation calculations.

way. Most other error rates are small for the total population, although for some demographic groups they are significant. For example, among men aged 25–59 who are out of the labor force, there is a 3.8 per cent probability of misclassification into employment. The demographic variation in error rates highlights the importance of disaggregating the flows before adjusting for classification errors.

These error probabilities, which we use to adjust the gross changes data, may be subject to a number of potential biases. Some of these understate the true error rate. For example, reinterviewers are instructed to try to interview the same person who was interviewed in the original survey. No similar practice is followed in successive months of the regular CPS survey, so it probably has higher response error rates than those reported here. In addition, if the reinterview procedure fails to identify an individual's true labor market status, our estimates of response error will be too small.

There are also biases which work in the opposite direction. The Reinterview Survey may exaggerate the extent of error since a week is allowed to pass between the events being described and the survey week. Reinterviews are also conducted by different interviewers than the initial interview, while two consecutive CPS monthly interviews are typically conducted by the same interviewer. Finally, the Reinterview Survey is also more frequently conducted by phone than the regular CPS, and this may affect response errors.

2. ADJUSTING THE GROSS CHANGES DATA

This section describes our procedure for using the estimated error rates to adjust the reported gross changes. Let F_{ij} denote the measured flow from labor market state i to state j, while F^*_{ij} is the true flow. The notation $\hat{F}_{ij}$ will refer to our estimates of the true flows. We can use the $\{q_{ij}\}$ to relate the true and measured flows. For example, consider the measured flow from employment to unemployment. There are nine different combinations of actual labor market transitions and response errors which can lead an individual CPS respondent to be classified as making an $E \rightarrow U$ transition. By summing the total number of individuals in each of these nine categories, we obtain an expression for the total measured flow:

$$
\begin{aligned}
(7) \qquad F_{EU} = {} & q_{EE}q_{EU}F^*_{EE} + q_{EE}q_{UU}F^*_{EU} + q_{EE}q_{NU}F^*_{EN} \\
& + q_{UE}q_{EU}F^*_{UE} + q_{UE}q_{UU}F^*_{UU} + q_{UE}q_{NU}F^*_{UN} \\
& + q_{NE}q_{EU}F^*_{NE} + q_{NE}q_{UU}F^*_{NU} + q_{NE}q_{NU}F^*_{NN}.
\end{aligned}
$$

Regardless of his true labor market status, each individual has *some* chance of being recorded as making an $E \rightarrow U$ transition. Of course, for some individuals this probability is trivial. The number of individuals who in fact make $U \rightarrow E$ transitions but are twice misclassified, first into employment (when they are unemployed) and then into unemployment (when they are employed), is likely to be quite small. The main contribution to the sum in (7) will come from the terms involving diagonal elements of the Q matrix.

Equation (7) may be written more generally as

$$(8)\qquad F_{kl}=\sum_i \sum_j q_{ik}q_{jl}F^*_{ij}.$$

We define F to be the 3×3 matrix of observed flows:

$$(9)\qquad F=\begin{bmatrix} F_{EE} & F_{EU} & F_{EN} \\ F_{UE} & F_{UU} & F_{UN} \\ F_{NE} & F_{NU} & F_{NN} \end{bmatrix}.$$

The system of equations in (8) can be compactly written in matrix form as

$$(10)\qquad F=Q'F^*Q$$

where Q is the matrix of classification error probabilities $\{q_{ij}\}$ and F^* is the matrix of true flows. Equation (10) expresses the observed flows as a function of the unobserved true flows and the classification error probabilities. It can be solved for the true flows:

$$(11)\qquad F^*=(Q^{-1})'FQ^{-1}.$$

Using our estimates $\{\hat{q}_{ij}\}$ to form $\hat{Q}$, we estimate the true flows as

$$(12)\qquad \hat{F}=(\hat{Q}^{-1})'F\hat{Q}^{-1}.$$

Both aggregate gross flows and those for each demographic group can be modified to yield a set of "response-error corrected" gross flows. We also calculate standard errors for the adjusted flows, again using a bootstrap procedure.[8]

An illustration of our adjustment procedure using the total flows, aggregating over all demographic groups, is shown in Table IV. The table's first panel reports the annual average unadjusted flows for the period January, 1977 to December, 1982. The table's next panel, labelled "Adjusted Flows, Without Raking," reports the adjusted gross flows calculated using equation (12). Some flows, particularly those involving transitions into and out of the labor force, change dramatically. There is a clear reduction in the number of individuals who are off the diagonal of the flow matrix. While 12.60 million transitions are recorded in the actual gross flow data, our adjusted matrix shows only 5.20 million transitions. This decline in the off-diagonal flows implies a reduction in the escape probabilities from each labor market state. A more complete discussion of the implications for labor market dynamics is provided in Section 4.

The differences between the adjusted and the unadjusted flows are large relative to the standard errors of the adjusted flows. For the $U\rightarrow N$ flow, for example, the estimated change is nine times its standard error. Equally significant changes take place in the $N\rightarrow E$ and $E\rightarrow N$ flows.

[8] The standard errors for the adjusted flows were computed by calculating synthetic adjusted flows corresponding to each of the 1000 synthetic sets of response error probabilities. The reported standard errors are the standard deviations of these 1000 draws. Similar calculations are used to compute the standard errors for the transition probabilities.

TABLE IV

TOTAL LABOR MARKET GROSS FLOWS WITH AND WITHOUT ADJUSTMENT[a]

	Unadjusted Flows Final State		
Initial State	Employed	Unemployed	NILF
Employed	91,865	1,652	3,157
Unemployed	1,857	3,899	1,521
NILF	2,805	1,610	55,541

	Adjusted Flows, Without Raking Final State		
Initial State	Employed	Unemployed	NILF
Employed	96,040	1,143	748
	(761)	(88)	(211)
Unemployed	1,395	5,391	723
	(89)	(147)	(89)
NILF	347	836	57,282
	(213)	(88)	(410)

	Adjusted Flows, Raked Final State		
Initial State	Employed	Unemployed	NILF
Employed	94,361	1,134	668
	(686)	(81)	(204)
Unemployed	1,413	5,517	666
	(80)	(104)	(90)
NILF	388	945	58,283
	(228)	(94)	(435)

[a] Unadjusted flows (denominated in thousands of persons) are annual averages for 1977–1982, drawn from unpublished BLS tabulations. Adjusted flows are calculated using the procedures outlined in the text. Standard errors for the adjusted flows are reported in parentheses.

The procedure described above does not impose any restrictions on the number of individuals in each labor market state before and after the flow adjustment. Nor does it constrain the estimated flow data to be consistent with observed changes in labor market stocks. The adjustment procedure substantially lowers the number of individuals classified as NILF and raises the number of unemployed. In the unadjusted data, there are 59.96 million individuals out of the labor force and 7.27 million unemployed. In the adjusted data, however, the number of individuals who are not in the labor force declines to 58.46 million, while the number of unemployed rises to 7.53 million.

To modify our adjusted flows to yield the same marginal totals as those implied by labor market stock data, we use the method of iterative proportional fitting, or "raking." This procedure, due to Deming and Stephan (1940), adjusts the cell proportions of a contingency table to agree with a pre-specified set of marginal totals by minimizing a weighted sum of squared deviations between the initial and "raked" proportions. The adjusted, raked flows, $\tilde{F}_{ij}$, minimize

$$(13) \qquad S=\sum_i\sum_j(\tilde{F}_{ij}-\hat{F}_{ij})^2/\hat{F}_{ij} \quad \text{subject to} \quad \sum_j \tilde{F}_{ji}=\sum_j \tilde{F}_{ij}=M_i$$

where M_i designates the required marginal total. We rake the adjusted flows, using an iterative procedure suggested by Deming and Stephan (1940), to conform with the marginal totals implied by the average labor market stocks for 1977–1982 as reported in the January issues of *Employment and Earnings.*

Our raked, adjusted flows are reported in the third panel of Table IV. The raking adjustments lead to substantial changes in some of the flows. For example, the estimated $E \rightarrow E$ flow declines by over one and one half million persons, while the $N \rightarrow N$ flow rises by one million. The marginal labor market stocks are also affected. The aggregate unemployment rate changes from 7.1 per cent to 7.3 per cent, and the labor force participation rate declines from 64.3 per cent to 63.5 per cent. The transition probabilities between labor market states are, however, virtually unaffected by the raking procedure. The largest change in a transition probability is that for p_{UU}, which rises from .717 to .725.[9]

3. ROBUSTNESS

The standard errors associated with the estimates suggest that they are quite reliable given the assumptions of our adjustment method. It remains to be seen whether our estimates are robust with respect to changes in these assumptions. We focus on our primary maintained assumption, the serial independence of response error probabilities for each individual. It seems plausible that persons who make an error in month t are more likely than others to make errors in month $t+1$, either because individuals differ in their error-proneness or because individuals in ambiguous circumstances are likely to make similar mistakes in successive months. Either of these possibilities can be modelled by allowing for heterogeneity in individual error probabilities.

We examine the robustness of our procedures by relaxing our earlier assumption that all individuals have identical error rates. While these experiments provide some evidence on the sensitivity of our results, they are restricted in focussing on only one specification of serial dependence. Other stochastic models for response errors might generate different results.

We postulate two classes of survey respondents who differ in their rates of survey response error. Individuals in the first class, who account for 100α per cent of the population, have error rates $q_{ij}^{(1)}=\lambda_1 q_{ij}$, $i \neq j$, where q_{ij} is the full-sample

[9] Our raking procedure minimizes (by design) the importance of margin adjustments. Previous attempts to treat both the adjustment and response error problems simultaneously, such as Abowd and Zellner (1985a, b), suggest that margin error corrections may be less important than response error corrections for analyzing labor market dynamics. Abowd and Zellner (1985a) show that although margin corrections can substantially alter the *size* of labor market flows, their effect on the associated transition probabilities is generally much smaller than the response error correction. Their findings are not conclusive, however, because Abowd and Zellner rely on a particular stochastic structure for the missing data process. Alternative approaches to either the margin-error or missing-data problems might lead to larger changes; future research should consider these questions.

error rate. For the second class, $q_{ij}^{(2)} = \lambda_2 q_{ij}$, $i \neq j$. To preserve population error rates, we require $\alpha\lambda_1 + (1-\alpha)\lambda_2 = 1$.

This heterogeneity assumption will clearly generate serial correlation in the errors. It also requires modifying (12), the adjustment formula. Define Q_1 as the error matrix with terms $q_{ij}^{(1)}$ off the diagonal and $q_{ii}^{(1)} = 1 - \sum_{j \neq i} q_{ij}^{(1)}$ on the diagonal, and define Q_2 similarly. With heterogeneity, the observed flow matrix is related to the true flow matrix F^* by

$$F = \alpha Q_1' F^* Q_1 + (1-\alpha) Q_2' F^* Q_2. \tag{14}$$

This matrix equation may be rewritten using the vec operator which stacks the columns of a matrix one upon each other. Since $\mathrm{vec}(ABC) = (C' \otimes A)\,\mathrm{vec}(B)$,

$$\mathrm{vec}(F) = [\alpha(Q_1' \otimes Q_1') + (1-\alpha)(Q_2' \otimes Q_2')]\,\mathrm{vec}(F^*) \tag{15}$$

so that

$$\mathrm{vec}(F^*) = [\alpha(Q_1' \otimes Q_1') + (1-\alpha)(Q_2' \otimes Q_2')]^{-1}\,\mathrm{vec}(F). \tag{16}$$

We calculated these adjusted flows for various specifications of α, λ_1, and λ_2, and found that allowing for heterogeneity of this type had relatively little impact on our results. For example, assuming that $\alpha = .5$, $\lambda_1 = 2$, and $\lambda_2 = 0$, the probability that an individual makes an error in period t, conditional upon an error at $t-1$, is 3.4 times as great as the probability of an error at t conditional on a correct response at $t-1$. The comparable value is 1.7 in a homogeneous population. In spite of this substantial change in the serial correlation pattern of the errors, the adjusted flows are changed relatively little from the homogeneous case. The most affected values move only sixteen per cent of the distance towards their unadjusted values. Even in the more extreme case in which one class of respondents is error free and the other has an error rate five times the population average, which makes the error rate conditional on a lagged error 8.2 times the error rate conditional on a correct lagged response, the average adjustment is .72 times the change in the homogeneous (no serial correlation) case.[10]

Our procedures do not treat the problem of attrition bias in the gross flows data or the problems that arise because individuals move from one demographic category to another as they age. Raking the data into conformity with the observed labor market stocks is a crude way of treating these problems which can lead to systematic biases in the flows data. The work of Abowd and Zellner (1985a, b) and Stasny and Feinberg (1985), which focuses on the missing data problem, and Fuller and Chua (1983, 1985), which treats the population flow problem, suggests that these issues are of some consequence.

[10] The adjusted flows taking account of heterogeneity with type I respondents twice as error-prone as the population average were *EE*, 95965, *EU*, 1189, *EN*, 776, *UE*, 1439, *UU*, 5218, *UN*, 850, *NE*, 377, *NU*, 962, and *NN*, 57126. With the type I persons five times as error-prone as the population average, the flows were *EE*, 95762, *EU*, 1318, *EN*, 852, *UE*, 1564, *UU*, 4764, *UN*, 1180, *NE*, 456, *NU*, 1288, and *NN*, 56721. These should be compared with the flows in the second panel of Table IV. Although two of the flows moved 61 per cent and 54 per cent of the distance back toward their unadjusted values, some of the other flows were hardly changed at all. Some sense of the changes in transition rates affecting unemployment durations can be obtained from the following. In the unadjusted data, p_{UU} is .536. In the adjusted data with no serial correlation correction, this probability is .726. In the two serial correlation cases presented here, it is .695 and .635 respectively.

While we regard the findings of our heterogeneity analysis as suggestive, they are not definitive. We consider only one form of serial correlation, and in particular, we have not allowed for differential persistence of different types of classification errors. Further research on the stochastic process which describes response errors must await longitudinal data matching both interviews and reinterviews in several consecutive months; these data are not currently available.

4. RESULTS

This section analyzes the results of applying our adjustment procedure to the gross changes data for seven disaggregated demographic groups: men 16–19, men 20–24, men 25–59, women 16–19, women 20–24, women 25–59, and teenagers of both sexes. In each case the estimates of $\{q_{ij}\}$ presented in Table III are used to adjust the annual average gross changes data for the period 1977–1982. Because most questions of labor market dynamics hinge on the transition probabilities derived from the gross changes data, Table V presents the transition probabilities corresponding to each group. These probabilities are estimated as:

$$\hat{p}_{ij} = \Pr(\text{status at } t+1 = j \,|\, \text{status at } t = i) = F_{ij} \Big/ \sum_k F_{ik}. \tag{17}$$

Probabilities from both the unadjusted and the raked adjusted flows are shown, along with the estimated standard errors for the adjusted probabilities. Table V shows that for smaller demographic groups, the standard errors of our adjustments are in some cases nontrivial relative to the differences between the raw and adjusted probabilities.

The disaggregated probabilities reveal a difficulty with our adjustment procedure: the adjusted flows are not constrained to be positive. For men 25–29, our adjustments make the $E \to N$ and $N \to E$ flows negative, although the standard errors of the adjusted flows are large. In the $E \to N$ case, the standard error is as large as the adjusted flow; the $N \to E$ standard error is two-thirds the size of the adjusted flow. In both cases, the ninety-five per cent confidence interval for the adjusted flow includes positive values. Our excessive adjustments for some groups may be due to serial correlation of reporting errors, although allowing for heterogeneity as in the last section still generates negative flows. The source and treatment of the negative flow problem should be addressed in future work. The finding, however, demonstrates the importance of demographic disaggregation in manipulating the gross flows data. Analyses which use either aggregate flows or distinguish only men and women, such as Abowd and Zellner (1985a, b) and Fuller and Chua (1985), fail to discover this problem.

The transition probabilities can be used to calculate several summary statistics for labor market activity. These include the expected duration of a completed spell in each labor market state, the probability of an unemployment spell ending in employment, and the probability of labor force withdrawal within a given month. Expected durations of completed spells are calculated as the reciprocal of the exit probability from each state. The probability of an unemployment spell

TABLE V

LABOR MARKET TRANSITION PROBABILITIES FROM ADJUSTED AND UNADJUSTED FLOWS[a]

Total, Unadjusted				Total, Adjusted and Raked			
	E	U	N		E	U	N
E	.950	.017	.033	E	.981	.012	.007
					(.002)	(.001)	(.002)
U	.255	.536	.209	U	.186	.726	.088
					(.010)	(.013)	(.012)
N	.047	.027	.926	N	.007	.016	.978
					(.004)	(.002)	(.004)

Men 16–19, Unadjusted				Men 16–19, Adjusted and Raked			
	E	U	N		E	U	N
E	.845	.049	.106	E	.901	.031	.068
					(.016)	(.009)	(.014)
U	.263	.454	.283	U	.183	.608	.209
					(.039)	(.049)	(.036)
N	.127	.088	.785	N	.071	.071	.857
					(.017)	(.010)	(.021)

Men 20–24, Unadjusted				Men 20–24, Adjusted and Raked			
	E	U	N		E	U	N
E	.934	.035	.031	E	.963	.016	.021
					(.015)[b]	(.007)	(.006)
U	.290	.581	.129	U	.172	.814	.013
					(.051)	(.065)	(.054)
N	.109	.073	.817	N	.072	.023	.905
					(.032)	(.039)	(.069)

Men 25–59, Unadjusted				Men 25–59, Adjusted not Raked[c]			
	E	U	N		E	U	N
E	.979	.014	.007	E	.993	.010	−.003
					(.008)	(.002)	(.003)
U	.347	.537	.116	U	.261	.725	.014
					(.042)	(.001)	(.043)
N	.081	.057	.862	N	−.048	.007	1.041
					(.031)	(.020)	(.041)

Women 16–19, Unadjusted				Women 16–19, Adjusted and Raked			
	E	U	N		E	U	N
E	.848	.038	.114	E	.897	.033	.070
					(.015)	(.007)	(.015)
U	.247	.423	.330	U	.219	.559	.222
					(.028)	(.042)	(.041)
N	.100	.078	.822	N	.050	.060	.890
					(.013)	(.008)	(.017)

Women 20–24, Unadjusted				Women 20–24, Adjusted and Raked			
	E	U	N		E	U	N
E	.927	.049	.023	E	.969	.014	.016
					(.018)[b]	(.006)	(.009)
U	.256	.505	.238	U	.185	.662	.154
					(.048)	(.065)	(.004)
N	.083	.065	.852	N	.016	.053	.931
					(.019)	(.009)	(.023)

TABLE V, CONT.

	Women 25-59, Unadjusted				Women 25-59, Adjusted and Raked		
	E	*U*	*N*		*E*	*U*	*N*
E	.951	.012	.037	*E*	.979	.009	.011
					(.003)	(.001)	(.003)
U	.225	.519	.256	*U*	.178	.733	.089
					(.017)	(.036)	(.030)
N	.050	.025	.925	*N*	.014	.011	.975
					(.005)	(.003)	(.005)
	Both Sexes 16-19, Unadjusted				Both Sexes 16-19, Adjusted and Raked		
	E	*U*	*N*		*E*	*U*	*N*
E	.846	.043	.110	*E*	.899	.032	.069
					(.010)	(.006)	(.008)
U	.255	.440	.305	*U*	.200	.584	.216
					(.023)	(.030)	(.027)
N	.112	.082	.805	*N*	.059	.065	.875
					(.009)	(.006)	(.011)

[a] Unadjusted probabilities are calculated from Gross Changes data for 1977-1982. Adjusted flows are described in text; standard errors are in parentheses.
[b] Some of the unraked flows constructed using the synthetic data sets in our "bootstrap" procedure yielded negative flows. This prevented us from using the raking algorithm. Standard errors are based on the standard errors for the unraked flows.
[c] For men 25-59, the adjusted flows yielded some negative values. We were therefore unable to rake the flows to conformity with labor market stocks. Unraked flows were used to calculate these probabilities and their standard errors.

ending in employment entry is $p_{UE}/(p_{UE}+p_{UN})$. The probability of labor force withdrawal is $(p_{UN}\Pi_U+p_{EN}\Pi_E)/(\Pi_U+\Pi_E)$, where Π_E and Π_U denote, respectively, the fraction of the population employed and unemployed.

Marston (1976) presents a complete analysis of the transition matrix differences between demographic groups. Two central conclusions of his analysis are the importance of transitions into and out of the labor force, and the great extent of turnover in the labor market. We focus on the extent to which these conclusions are modified by our adjusted data, and then comment on the implications of our findings for analyses which explore labor market dynamics without making explicit reference to the gross changes data.

Table VI presents estimates of the monthly probability of labor market withdrawal for different demographic groups, estimated from our unadjusted and adjusted data. The unadjusted data imply that over forty per cent of the labor force can be expected to withdraw within a year. The unadjusted data also show that among those leaving employment, labor force withdrawal is almost twice as common as unemployment.[11] Perhaps most significant, the unadjusted data imply that almost half (45 per cent) of unemployment spells end in labor force withdrawal. Table VI reports values of one minus this probability, the chance that conditional upon escaping from unemployment the individual finds a job. For women aged 25-59, for example, forty-six per cent of unemployment spells end in successful job-finding.

[11] This calculation is based on the conditional probability of leaving the labor force given a transition out of employment, $p_{EN}/(p_{EN}+p_{EU})$.

TABLE VI

PROBABILITIES OF LABOR FORCE WITHDRAWAL AND SUCCESSFUL UNEMPLOYMENT ESCAPE[a]

Demographic Group	Probability of Labor Force Withdrawal: Unadjusted Flows	Probability of Labor Force Withdrawal: Raked Adjusted Flows	Probability of Labor Force Withdrawal: Percentage Change	Probability of Successful Escape from Unemployment: Unadjusted Flows	Probability of Successful Escape from Unemployment: Raked Adjusted Flows	Probability of Successful Escape from Unemployment: Percentage Change
Total	.044	.013	−71.4%	.550	.680	23.6%
Men 16–19	.138	.094	−31.8%	.481	.467	−2.9%
Men 20–24	.042	.016	−62.4%	.692	.928	34.1%
Men 25–59	.011	—	—	.749	—	—
Women 16–19	.151	.098	−35.0%	.428	.497	16.1%
Women 20–24	.069	.031	−54.3%	.518	.546	5.4%
Women 25–59	.049	.016	−67.6%	.467	.667	42.7%
Both Sexes, 16–19	.146	.096	−34.4%	.455	.481	5.7%

[a] The probability of labor force withdrawal is $(p_{EN}\Pi_E + p_{UN}\Pi_U)/(\Pi_E + \Pi_U)$, while the probability of successful unemployment escape is $p_{UE}/(p_{UE} + p_{UN})$. The calculations are based on probabilities in Table V. For the men 25–59 group, the negative probabilities prevented calculations.

The Reinterview Survey suggests that spurious reporting of labor force withdrawal is the most common form of reporting error. It is therefore not surprising that the adjusted data present a very different view of the importance of labor force withdrawal. The overall withdrawal rate for the entire population is only about one-third as great as that suggested by the unadjusted data. In contrast to the adjusted data, job leaving to unemployment is twice as common as job leaving followed by labor force withdrawal. The adjusted data also imply that about two-thirds of the unemployed end their spell of unemployment by finding a job.

The difference between the unadjusted and adjusted probabilities varies across demographic groups. For men 20–24, for example, there is a sixty-two per cent reduction in withdrawal probabilities. Male teenagers, who exhibit somewhat higher mobility, experience only a thirty per cent reduction as a result of flow adjustment. The probability of a successful escape from unemployment rises for nearly all demographic groups, with the most pronounced changes for the least mobile groups.

A second striking feature of the unadjusted data is the very high rate of implied labor force turnover. Table VII illustrates this by presenting estimates of unemployment durations. For the entire population, the unadjusted data suggest that the mean duration of unemployment is only about 2.2 months. For women the estimated durations are shorter and for teenagers they are far shorter, 1.8 months. The adjusted data tell a rather different story. For the entire population the estimated duration of a completed unemployment spell is 3.6 months, almost two-thirds greater. For women, the expected spell duration rises from 2.0 to 3.1 months, while for men the change is even more pronounced, 2.4 to 4.5 months.[12] Our adjustments accentuate the differences between teenagers and the remainder

[12] The results for both male and female aggregates are based on adjusted transition probabilities not reported in Table V.

TABLE VII
EXPECTED UNEMPLOYMENT DURATIONS[a]

Demographic Group	Expected Unemployment Duration (Months) Calculated From: Unadjusted Flows	Raked Adjusted Flows	Percentage Change
Total	2.15	3.65	69.6%
Men 16-19	1.83	2.56	39.7%
Men 20-24	2.38	5.39	126.3%
Men 25-59	2.16	3.63	68.4%
Women 16-19	1.73	2.27	31.1%
Women 20-24	2.02	2.96	46.3%
Women 25-59	2.08	3.75	80.3%
Both Sexes, 16-19	1.79	2.40	34.7%

[a] Expected unemployment durations are $1/(1-P_{UU})$. Calculations are based on probabilities reported in Table V. For men 25-59, unraked adjusted flows are used as in Table V.

of the population, because they revise upwards the teenagers' durations of unemployment by only small amounts.

Response error adjustments have their most dramatic effects on those groups whose labor market behavior is least dynamic. If error rates are relatively constant across demographic groups, then eliminating errors will have the greatest proportional effect on groups whose members make the fewest transitions. The point is exemplified by considering the male 25-59 group. Here the estimated duration of unemployment rises from 2.2 months to 3.6 months. Unfortunately, these results must be discounted because some of the adjusted flow probabilities are negative.

Correction for reporting errors which lead to overestimates of close to seventy per cent in the escape rate from unemployment is likely to increase reasonable estimates of any unemployment duration measure. Even estimates such as those of Clark and Summers (1979a, b) may underestimate the true extent of concentration in unemployment. Some support for our suggestion that unemployment spells are longer than usually shown in the gross changes data derives from non-CPS sources of labor market information, usually retrospective surveys of individual experience, which often find longer spell lengths for all labor market states than those reported by the CPS.[13] While interpretation of these facts is complicated by the varying definitions of unemployment used on non-CPS surveys, they tend to corroborate our findings.

Our results suggest that the unadjusted gross changes data may lead to misleading inferences about the character of the labor market. We suspect that similar problems plague efforts to use the gross changes data to study cyclical phenomena. In particular, conventional analyses may understate the cyclicality of labor market flows because a relatively constant number of spurious flows are added in all periods to the cyclically variable true flows.

[13] Clark and Summers (1979b) discuss some of this evidence.

Our results also cast doubt on conventional analyses of unemployment which do not make explicit use of the gross changes data. One common method for analyzing unemployment durations, pioneered by Kaitz (1970) and Salant (1977), involves inferring the distribution of completed spell lengths from published information on the distribution of interrupted spell lengths. A simple procedure of this type is to estimate the mean duration of completed spell lengths by dividing the number of unemployed persons by an estimate of the flow rate into unemployment, based for example on the number of persons unemployed less than 5 weeks.[14] For 1981 this procedure yields a mean duration of completed unemployment spells of 2.4 months, very close to the estimate produced by the unadjusted gross changes data.

The reason this procedure goes wrong should be clear. Errors in classification lead a large number of persons to be spuriously classified as unemployed, artificially inflating the stock of short term unemployed. Likewise, many of the longer term unemployed are spuriously not measured as unemployed. While these two biases do not have a large effect on the measured stock of unemployed persons because they offset, both biases reduce the mean reported duration of unemployment.

Related difficulties plague studies of the transition out of unemployment which use the techniques of survival analysis, such as Lancaster (1979) and Flinn and Heckman (1982). Some transitions out of unemployment are spurious, and some continuing spells of unemployment are recorded as ending. Estimated hazard functions correspond not to the probability of escaping unemployment, but to the probability of being *measured* as leaving unemployment. The latter may be the outcome of either a classification error or a genuine labor market transition, complicating the structural interpretation of hazard models.[15]

5. CONCLUSIONS

This paper develops a procedure for adjusting the Current Population Survey gross changes data for reporting errors. Although our findings are not definitive because our procedure makes particular assumptions about the stochastic process generating response errors, the corrected data suggest that the labor market may be much less dynamic than has frequently been suggested. Conventional measures may understate the duration of unemployment by as much as eighty per cent and overstate the extent of movement into and out of the labor force by several hundred per cent. The use of our adjusted data also throw demographic differences in patterns of labor market dynamics into sharp relief.

This research could usefully be extended in several directions. Alternative procedures for estimating CPS error rates could be devised to relax the assumption

[14] This technique is used by Darby, Haltiwanger, and Plant (1985).

[15] Further difficulties affect procedures which rely upon individuals reporting unemployment durations since these data are extremely unreliable. In Poterba and Summers (1984) we demonstrate that only about a quarter of the population gives consistent responses in successive months to questions about the duration of unemployment. A related discussion of survival analysis in the presence of measurement error may be found in Stasny (1983).

that the reconciliation process correctly estimates individuals' true labor force status. Error probabilities could also be estimated imposing the constraint that the marginal labor market stocks estimated in the CPS are unbiased estimates of the true stocks. Alternative procedures to adjust the actual gross changes data could also be developed.

Our findings suggest that measurement errors distort estimates of basic statistics characterizing the labor market. Statistical techniques for analyzing labor market data which take account of pervasive measurement errors need to be developed. Because of the discrete nature of data on labor market status, and its longitudinal character, standard techniques for the treatment of errors in variables are not applicable. In work now underway (Poterba and Summers (1986)), we are developing a multinomial logit procedure for analyzing labor market transitions which are reported with error.

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Manuscript received September 1984; final revision received February, 1986.

REFERENCES

ABOWD, J., AND A. ZELLNER (1985a): "Estimating Gross Labor Force Flows," *Journal of Economic and Business Statistics*, 3, 254–283.

——— (1985b): "Application of Adjustment Techniques to U.S. Gross Flow Data," in *Proceedings of the Conference on Gross Flows in Labor Force Statistics*. Washington, D.C.: U.S. Government Printing Office.

AKERLOF, G., AND B. MAIN (1980): "Unemployment Spells and Unemployment Experience," *American Economic Review*, 70, 885–893.

BUREAU OF THE CENSUS (1969): *The Current Population Survey Reinterview Program: January* 1961 *through December* 1966. Washington, D.C.: U.S. Government Printing Office, Census Bureau Technical Paper No. 19.

CLARK, K. B., AND L. H. SUMMERS (1979a): "Labor Market Dynamics and Unemployment: A Reconsideration," *Brookings Papers on Economic Activity*, 2, 13–60.

——— (1979b): "Labor Force Transitions and Unemployment," National Bureau of Economic Research Working Paper 277, Cambridge, MA.

DARBY, M., J. HALTIWANGER, AND M. PLANT (1985): "Unemployment Rate Dynamics and Persistent Unemployment Under Rational Expectations," *American Economic Review*, 75, 614–637.

DEMING, W. E., AND F. F. STEPHAN (1940): "On a Least Squares Adjustment of a Sampled Frequency Table When the Expected Marginal Totals Are Known," *Annals of Mathematical Statistics*, 11, 427–444.

EFRON, B. (1982): *The Jackknife, the Bootstrap, and Other Resampling Plans*. Philadelphia: Society for Industrial and Applied Mathematics.

FELDSTEIN, M. S. (1973): *Lowering the Permanent Rate of Unemployment*. Washington, D.C.: U.S. Government Printing Office.

FLINN, C., AND J. HECKMAN (1982): "Models for the Analysis of Labor Market Dynamics," in *Advances in Econometrics*, ed. by R. Basmann and G. Rhodes. Greenwich, Conn.: JAI Press.

FULLER, W. A., AND T. C. CHUA (1983): "A Model of Multinomial Response Error," U.S. Bureau of the Census, Washington, D.C., unpublished report.

——— (1985): "Gross Change Estimation in the Presence of Response Error," in *Proceedings of the Conference on Gross Flows in Labor Force Statistics*. Washington, D.C.: U.S. Government Printing Office.

GRAHAM, D. W. (1979): "Estimation, Interpretation, and Use of Response Error Measurements," U.S. Commerce Department, Washington, D.C., unpublished memorandum.

HALL, R. E. (1972): "Turnover in the Labor Force," *Brookings Papers on Economic Activity*, 3, 709-756.

KAITZ, H. B. (1970): "Analyzing the Length of Spells of Unemployment," *Monthly Labor Review*, 93, 11-20.

LANCASTER, T. (1978): "Econometric Methods for the Duration of Unemployment," *Econometrica*, 47, 939-956.

MARSTON, S. I. (1976): "Employment Instability and High Unemployment Rates," *Brookings Papers on Economic Activity*, 1, 169-210.

NATIONAL COMMISSION ON EMPLOYMENT AND UNEMPLOYMENT (1979): *Counting the Labor Force.* Washington, D.C.: U.S. Government Printing Office.

POTERBA, J. M., AND L. H. SUMMERS (1984): "Survey Response Variation in the Current Population Survey," *Monthly Labor Review*, 107, 31-37.

——— (1986): "Multinomial Logit with Errors in Classification," Cambridge, MA, unpublished.

SALANT, S. W. (1977): "Search Theory and Duration Data: A Theory of Sorts," *Quarterly Journal of Economics*, 91, 39-57.

SCHREINER, I. (1980): "Reinterview Results from the CPS Independent Reconciliation Experiment," Bureau of the Census, Washington, D.C. unpublished manuscript.

SMITH, R. E. (1973): "Dynamic Determinants of Labor Force Participation: Some Evidence from Gross Change Data," The Urban Institute, Washington, D.C., Working Paper 350-49.

SMITH, R. E., AND J. VANSKI (1979a): "Gross Change Data: The Neglected Data Base," in *Report of the National Commission on Employment and Unemployment, Appendix Volume II.* Washington, D.C.: Government Printing Office.

——— (1979b): "The Volatility of the Teenage Labor Force Entry, Exit, and Employment Flows," paper presented at the conference on Employment Statistics and Youth, sponsored by the U.S. Department of Labor, February 11, 1979.

STASNY, E. A. (1983): "Estimating Gross Flows in Labor Force Participation Using Data from the Canadian Labor Force Survey," Ph.D. dissertation, Department of Statistics, Carnegie-Mellon University.

STASNY, E. A., AND S. E. FEINBERG (1985): "Some Stochastic Models for Estimating Gross Flows in the Presence of Nonrandom Response," in *Proceedings of the Conference on Gross Flows in Labor Force Statistics.* Washington, D.C.: U.S. Government Printing Office.

WOLTMAN, H., AND I. SHREINER (1979): "Possible Effects of Response Variance on the Gross Changes Data," Bureau of the Census, Washington, D.C., unpublished memorandum.