NBER WORKING PAPER SERIES

UNEMPLOYMENT BENEFITS, LABOR MARKET TRANSITIONS, AND SPURIOUS FLOWS: A MULTINOMIAL LOGIT MODEL WITH ERRORS IN CLASSIFICATION

James M. Poterba

Lawrence H. Summers

Working Paper No. 4434

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 1993

This is a revised version of a manuscript of the same title dated October, 1982. We are grateful to the NSF and NBER for financial support, to Dan Feenberg, Jonathan Gruber, and Jerry Hausman for helpful comments, and to Irv Schreiner of the Census Bureau for providing us with unpublished data. This paper is part of NBER's research program in Public Economics. Any opinions expressed are those of the authors and should not be attributed to any institutions with which they are affiliated.

NBER Working Paper #4434
August 1993

UNEMPLOYMENT BENEFITS, LABOR MARKET TRANSITIONS, AND SPURIOUS FLOWS: A MULTINOMIAL LOGIT MODEL WITH ERRORS IN CLASSIFICATION

ABSTRACT

This paper develops an algorithm for analyzing discrete events, such as labor market transitions, when some of these transitions are spurious because of measurement errors. Our algorithm extends the standard multinomial logit model, although our basic approach could be used with other stochastic models as well. We apply this algorithm to study the effect of unemployment insurance (UI) on transitions from unemployment to employment and out of the labor force. Our results suggest that UI lengthens unemployment spells by reducing both transition rates, and show that correcting for measurement error strengthens the apparent effect of UI on spell durations.

James M. Poterba
Department of Economics
Room E52-350
Massachusetts Institute of Technology
50 Memorial Drive
Cambridge, MA 02139
and NBER

Lawrence H. Summers
Under Secretary for International Affairs
Department of Treasury
Room 3432
1500 Pennsylvania Avenue, NW
Washington, DC 20220
and NBER

Many studies have focused on the determinants of an unemployed individual's probability of finding a job, attempting to measure the effects of individual characteristics, receipt of government transfers, unemployment benefits, job search activity, and reservation wages on this transition probability. Others have sought to determine the average duration of unemployment spells, relying upon estimated probabilities of movement between the categories of unemployment, employment, and not-in-the-labor force. Atkinson and Micklewright (1991) provide a recent survey of this substantial literature. Very few of these studies, however, have allowed for the possibility of response error in an individual's reported status.

Response errors are a problem in all research utilizing sample surveys. Significant rates of response error have substantial implications for research on labor market dynamics, since they result in spurious transitions between labor market states.[1] Estimates of an individual's probability of leaving unemployment, computed from survey data, will overstate the probability that the individual either finds a job or leaves the labor force. Proper estimation of an individual's transition probability requires explicit modelling of the response variation problem. In this paper, we investigate the importance of reporting errors for studies of labor market transitions. We develop a model of labor force transitions that allows for spurious transitions, and apply this model to studying the effect of unemployment insurance on the duration of unemployment.

We begin by examining the problem of response variation. In the first section,

---

[1]See Poterba and Summers (1984, 1986), Duncan and Hill (1985), and Bound et al (1990) for related discussions of measurement error in labor market data.

we describe the incidence of errors in the "employment status" questions in the Current Population Survey. Misclassification between the states "unemployed" and "not in the labor force" (NILF) appears to be a particularly substantial problem. The second section develops a probabilistic model for the labor market transitions of unemployed individuals, generalizing the multinomial logit model to allow for the possibility of misclassification. Our model assumes that the individual's true labor market status is observed at some point. Response errors therefore occur in only one of the two surveys that are used to compute transition probabilities. The probability that an individual who is known to be unemployed in the first survey is observed to move from unemployment to employment is the sum of the probability that he actually finds a job, and is correctly classified as unemployed, and the probability that he either remains unemployed or leaves the labor force but is misclassified as unemployed.

We estimate our model using data from matched CPS records for May and June 1976 along with information from the May 1976 Job Search Supplement to the Current Population Survey. We present our empirical results in Section Three. We focus on the effects of unemployment benefit receipt, and an individual's reservation wage, on his probability of finding employment. Unemployment insurance is shown to have a substantial effect in depressing re-employment probabilities and increasing the duration of unemployment spells. If UI replaces fifty percent of a worker's previous after tax earnings, the expected duration of his unemployment spell increases by one and one-half months, from 11 weeks to 17 weeks. There is also a significant reporting effect. Receipt of unemployment benefits requires that an individual remain in the labor force looking for work; this causes a substantial reduction in the labor force exit rate amongst individuals receiving U.I. While finding substantive effects for transfer programs, we find very small effects of reservation wages on re-employment probabilities. This may cast some doubt on the relevance of search-theoretic explanations of unemployment. There is a brief concluding section that interprets our findings and suggests directions for future work.

1. Employment Status Misreporting in the CPS

Reporting errors are a substantial problem in the Current Population Survey. The incidence of errors due to response and coding mistakes is well documented by the Census Bureau's Reinterview Surveys.[2] These surveys involve reinterviewing a subsample of the households included in the CPS and conducting new interviews. These secondary interviews typically occur about a week after the original survey. Respondents are asked, however, to describe their activities in the preceding week. In some cases, the "nonreconciled" component of the Reinterview Survey, there is no attempt to determine which, if either, of the two responses is correct. However, for the "Reconciled" subgroup of the Reinterview Survey, typically about one third of the reinterviewed households, the second interviewer compares the results on the first survey with the reinterview answers. Then, before leaving the household, he

[2]See Graham (1979), Woltman and Schreiner (1979), Census Bureau Technical Report No. 19 (1969), Poterba and Summers (1984, 1986), and Biemer and Forsman (1992).

attempts to decide which, if either, of any conflicting responses is correct.[3] The Reinterview responses for those in the reconciled subsample, therefore, are the "truth" as determined by the second interviewer.

The reconciled Reinterview Surveys permit analysis of employment status coding errors. Table 1, Error Matrix A shows the fraction of individuals in each employment category on the Reconciliation subgroup by their category on the first survey. While most of the employed CPS respondents are correctly classified, a substantial fraction of the unemployed individuals are reported in other categories. Ten percent of the truly unemployed were classified as not in the labor force (NILF) on the first survey. A further 3.6 percent were recorded as employed. The accuracy of responses by those truly out of the labor force was also quite high, with 99.2 percent correctly classified.

The finding that many unemployed individuals are misclassified is important for studies of unemployment dynamics. If nearly fifteen percent of unemployed individuals are incorrectly classified in a given month, then many of the transitions between labor force states may be spurious. In the extreme case, if individuals were never misclassified in two consecutive months and there were no true transitions, the expected duration of measured unemployment spells would be 26.7 weeks.[4] But in

[3]This fails to detect those individuals who report consistent, but incorrect, responses in both months. Bound and Krueger (1991) present evidence of positive persistence of measurement errors in CPS earnings data.

[4]The true mean spell duration for unemployed workers in this scenario is infinite. The calculation of expected measured spell length proceeds by finding the expected value of the geometric random variable X, the time at which the first non-U response occurs. The probability of this event is .15 in each month, and the

fact, workers who were unemployed would never find jobs or leave the labor force. All labor market flows would be caused by classification errors.

Error Matrix A describes the measurement error problem in the Current Population Survey as a whole. It does not reflect the errors associated with individuals who are unemployed in a particular month and then experience transitions. A substantial body of evidence suggests that many individuals, when monitored for three consecutive months in the CPS, report themselves as experiencing unemployment-labor force withdrawal-unemployment.[5] The U-N-U transitors also tend to report long spell durations at their third interview, suggesting that they perceive themselves as having experienced an ongoing spell of unemployment. While the reinterview survey reveals that only one quarter of one percent of NILF-reported individuals are actually unemployed, this is because many individuals are genuinely not in the labor force and are rather unlikely to be experiencing an unemployment spell.[6]

---

expected number of months until one transition is observed is 1/.15 = 6.66, or 26.7 weeks.

[5]See Clark and Summers (1979) and Poterba and Summers (1984) for discussion of the U-N-U transitions.

[6]Flinn and Heckman (1983) argue that the states of unemployment and NILF are well-defined and distinct. They draw evidence from the clear differences in the models explaining the probability of unemployed and NILF individuals becoming employed. However, this evidence is not relevant to understanding whether a large fraction of those who are unemployed drift in and out of the "NILF" category with little or no change in behavior. There are a large number of individuals, classified as NILF, who are not casual entrants to the labor force. Many persons are disabled, retired, or otherwise unfit or unable to work. They are conceptually distinct from the unemployed, who are searching for work. A small fraction of all NILF respondents, but a substantial fraction of NLF respondents who were unemployed in the preceding month, are searching for work and ready to accept a job. These are the miscategorized workers on whom we focus.

However, conditional upon having been unemployed the month before, the measurement error rates for the NILF category may be large.

Error Matrix B presents our conjecture of plausible measurement error rates conditional upon unemployment in the previous quarter. We double the probabilities of mis-response for individuals who are unemployed, and we introduce substantial error probabilities for those reported as NILF. In our estimation of transition probabilities, we tried both error matrices A and B to determine the effect of large error rates on our estimated coefficients.

Aggregate reinterview data provides very little information about whether measurement error probabilities differ across individuals. One subdivision of the reinterview survey that was available allowed us to calculate separate error probabilities for men and women. These are shown in Table 2. There is some evidence of differences in error rates. Women appear more likely to be categorized as NILF when they are unemployed, and employed women are also more likely than employed men to list themselves as out of the labor force. More men than women who are out of the labor force report themselves as unemployed or employed. In our empirical work, we use the aggregate error rate matrix of Table 1.

Our discovery of substantial error rates in the CPS raises several important issues for empirical investigations based on survey data. First, some allowance should be made for the prospect of response errors. This is especially true in studies which involve discrete choices, or which rely on survey questions which ask respondents to describe their activities at some previous time. The problem of response error may become acute when studies are focused on the difference in discrete variables reported in two surveys. Second, some allowance for spurious transitions must also be made in applying duration models to panel data on unemployment, as for example in Lancaster (1979), Flinn and Heckman (1982), and many subsequent studies. When some of the hazarded events occur because of response errors, the resulting hazard function parameter estimates will be inconsistent. In the next section we present a stochastic model of labor market transitions that explicitly treats the problem of response variation.

2. A Multinomial Logit Model with Classification Errors

The misclassification problem is difficult to treat in most panel data sources. Observed transitions between consecutive interview dates may arise from four sources. First, the individual may have reported correctly in both surveys and actually experienced a transition. Second, there will be spurious transitions by individuals who were misclassified on the first survey and correctly classified on the second. Symmetrically, the third type of transition is by individuals who were correctly classified on the first survey but misreported on the second. Finally, some observed transitions may be due to individuals who were misclassified on both surveys, but were misclassified in different ways on the two surveys. This myriad of possibilities makes the likelihood function for the observed outcomes rather complicated.

Estimation of a two-survey transition probability model is substantially easier if an individual's true status is known with certainty for one of the two surveys. If the respondent's first survey status is certain, then all of the observed transitions are either true transitions or the result of survey response error in the second period. We obtained a data set in which all of the individuals are known to have been unemployed in the first survey month, but whose subsequent labor market experience might have been recorded incorrectly.

To construct the likelihood function for the observed labor market transitions of a group of unemployed individuals, we make two assumptions. First, we assume that the probability of actual (and possibly unobserved) transitions to employment or out of the labor force are described by a multinomial logit model. For each individual, the probability of each type of transition depends upon a vector of individual characteristics X_i.

(1) $P_{UE|X_i}$ = Prob (Unemployed in May, Employed in June $|X_i)$ $= \dfrac{e^{-X\beta_1}}{1 + e^{-X\beta_1} + e^{-X\beta_2}}$

and

(2) $P_{UN|X_i}$ = Prob (Unemployed in May, NILF in June $|X_i)$ $= \dfrac{e^{-X\beta_2}}{1 + e^{-X\beta_1} + e^{X\beta_2}}$.

Second, the probability of reporting errors depends upon an individual's true labor market state but is otherwise independent of his characteristics. These error probabilities are denoted

(3) q_{ij} = Prob (Recorded State is j | True State is i).

There are nine misclassification probabilities in the three state model. However, only six are independent since the probabilities satisfy an adding up condition:

(4) $$q_{ii} = 1 - \sum_{j \neq i} q_{ij} \quad i = E, U, N.$$

The q_{ii} terms are the probabilities of correct reporting when the individual is in state i.

The likelihood function for observed outcomes involves combinations of the true transition probabilities and measurement error rates. For example, the probability that an individual with characteristics X_i is observed transiting from unemployment to employment is

(5) $$\tilde{P}_{UE|X_i} = q_{UE}P_{UU|X_i} + q_{EE}P_{UE|X_i} + q_{NE}P_{UN|X_i}$$

The notation $\tilde{P}_{ij}$ refers to the probability of <u>observing</u> a transition, while P_{ij} is the probability of an <u>actual</u> transition. The first term in (5) is the probability that the individual actually becomes employed and is correctly classified in the second survey. The next term measures the probability that the individual remained unemployed in the second month but was misclassified as having become employed. The final term is the probability that there was a transition out of the labor force which was actually recorded as a transition to employment. Thus, it involves both a transition and a reporting error. The relationship between actual and observed transition probabilities can be written compactly in matrix form

(6) $$\begin{bmatrix} \tilde{P}_{UU} \\ \tilde{P}_{UE} \\ \tilde{P}_{UN} \end{bmatrix} = \begin{bmatrix} q_{UU} & q_{EU} & q_{NU} \\ q_{UE} & q_{EE} & q_{NE} \\ q_{UN} & q_{EN} & q_{NN} \end{bmatrix} \begin{bmatrix} P_{UU} \\ P_{UE} \\ P_{UN} \end{bmatrix}.$$

Using the logit assumption, the probabilities of <u>observed</u> transitions may be written

$$\text{(7)}\qquad \begin{aligned}\tilde{P}_{UE|X_i} &= \frac{q_{UE}\cdot 1}{1+e^{-X\beta_1}+e^{-X\beta_2}} + \frac{q_{EE}\cdot e^{-X\beta_1}}{1+e^{-X\beta_1}+e^{X\beta_2}} + \frac{q_{NE}\cdot e^{-X\beta_2}}{1+e^{-X\beta_1}+e^{-X\beta_2}} \\ &= \frac{q_{UE}+(1-q_{EU}-q_{EN})e^{-X\beta_1}+q_{NE}e^{-X\beta_2}}{(1+e^{-X\beta_1}+e^{-X\beta_2})}.\end{aligned}$$

This expression, and its analogues for the other observed probabilities, forms the basis of our likelihood function.

The data sample is ordered so that individuals 1,..., N_1 are observed as unemployed in the second month, N_1 + 1,..., N_2 are classified as employed, and N_2 + 1,..., N are out of the labor force. The likelihood function is therefore

$$\text{(8)}\qquad L(\underset{\sim}{q},\beta_1,\beta_2) = \prod_{i=1}^{N_1} \tilde{P}_{UU|X_i} \prod_{i=N_1+1}^{N_2} \tilde{P}_{UE|X_i} \prod_{i=N_2+1}^{N} \tilde{P}_{UN|X_i}.$$

By substituting the expressions corresponding to (7) for both $\tilde{P}_{UE}$ and $\tilde{P}_{UN}$ into (8), we find

$$\text{(9)}\qquad \begin{aligned}L(\underset{\sim}{q},\beta_1,\beta_2) = &\prod_{i=1}^{N_1}\left[\frac{(1-q_{UE}-q_{UN})+q_{EU}e^{-X\beta_1}+q_{NU}e^{-X\beta_2}}{1+e^{-X\beta_1}+e^{-X\beta_2}}\right] \\ &\cdot \prod_{i=N_1+1}^{N_2}\left[\frac{q_{UE}+(1-q_{EU}-q_{EN})e^{-X\beta_1}+q_{NE}e^{-X\beta_2}}{1+e^{-X\beta_1}+e^{-X\beta_2}}\right] \\ &\cdot \prod_{i=N_2+1}^{N}\left[\frac{q_{UN}+q_{EN}e^{-X\beta_1}+(1-q_{NE}-q_{NU})e^{-X\beta_2}}{1+e^{-X\beta_1}+e^{-X\beta_2}}\right].\end{aligned}$$

The log likelihood function is therefore

$$\log L(\underline{q},\beta_1,\beta_2) = \sum_{i=1}^{N} -\log\left(1+e^{-X\beta_1}+e^{-X\beta_2}\right) + \sum_{i=1}^{N_1} \log\left[(1-q_{UE}-q_{UN}) + q_{EU}e^{-X\beta_1} + q_{NU}e^{-X\beta_2}\right]$$

$$(10) \qquad + \sum_{i=N_1+1}^{N_2} \left[q_{UE}+(1-q_{EU}-q_{EN})e^{-X\beta_1} + q_{NE}e^{-X\beta_2}\right]$$

$$+ \sum_{i=N_2+1}^{N} \left[q_{UN}+q_{EN}e^{-X\beta_1} + (1-q_{NE}-q_{NU})e^{-X\beta_2}\right].$$

A natural generalization of this model would allow for the response error rates to depend upon individual characteristics. In this case, $q_{ij|x}$ would be substituted for q_{ij} in the above expressions. In principle, parameters linking characteristics to error rates could be estimated.

In the constant error rate model, we consider the error rates $[q_{ij}]$ as parameters. We do not estimate them simultaneously with (β_1, β_2), but rather use the estimates of the error probabilities provided by the Reinterview Survey and proceed as though these are the true values of $[q_{ij}]$. Then, we maximize the conditional likelihood function of (β_1,β_2). This procedure enables us to sample the sensitivity of the estimated (β_1,β_2) with respect to changes in the measurement error rates.[7]

3. Data and Estimation

Our estimation of the transition probability model is based on a May 1976 study of the job search methods used by unemployed workers. A total of 4,668 persons

---

[7]The procedure ignores the sampling variability of the estimated error probabilities in computing the standard errors of β_j. This may affect inference about the true transition model parameters.

in the May 1976 CPS were classified as unemployed and asked to fill out a special supplementary questionnaire concerning previous work experience and earnings, current job-seeking methods, and employment aspirations.[8] In many households, the form was left to be filled in later or was mailed to the unemployed person after a telephone interview. The nonresponse rate was 31 percent and resulted in a total sample of 3,238 completed questionnaires.[9]

We assumed that all of the Job Search Questionnaire respondents were in fact unemployed, so that there were no reporting errors in the May data. Two arguments support this view. First, the surveyed individuals had all been recorded as unemployed in the May 1976 Current Population Survey. In addition, however, those who felt the questionnaire did not apply to them because they had already found a job or had stopped searching were allowed to return the survey unanswered. The remaining individuals, who persevered and answered a six page survey about their job seeking activities, seem very likely to be truly unemployed.

To analyze labor market transitions we combined information from the Job Search questionnaire with subsequent CPS interview data that documented labor market experience. Of the 3,238 Job Search Questionnaire respondents, 1,304 appeared on the CPS match tape which contained the regular CPS questionnaire for both May and June. This reduced our sample size considerably. In addition, some

---

[8]See Rosenfeld (1977) for a description of the survey and a copy of the questionnaire.

[9]This data set was used by Feldstein and Poterba (1984) in their investigation of reservation wages and unemployment insurance, and by Baron and Mellow (1981) in their transitions study.

individuals who answered the Job Search Survey did not provide information about their reservation wage or their previous wage. After excluding all individuals with missing data, our final sample contained 908 unemployed men and women.[10]

Two variables are particularly important in our modelling of the transition probability out of unemployment. The first is the ratio of an individual's reservation wage to his wage at last job.[11] Our measure of the reservation wage was based on the following pair of questions: (1) "What kind of work were you looking for (in the period April 18 through May 15)?" and (2) "What is the lowest wage or salary you would accept (before deductions) for this type of work?" Individuals who indicated that they were looking for more than one kind of work were asked to specify their reservation wage for the type of job that they preferred. We computed the ratio of this reservation wage to the wage that the individual described as "the usual earnings ... before deductions" on the "last job at which you worked for two consecutive weeks or more."[12]

---

[10]Since one of our explanatory variables is the ratio of the individual's reservation wage to his or her previous wage, we have eliminated from the sample all those individuals who are classified as new entrants (who have no previous wage) or reentrants (whose previous wage may refer to a much earlier period).

[11]A comprehensive survey of the principles of search theory may be found in Lippman and McCall (1976).

[12]Individuals may indicate their usual earnings as a rate per hour, per week, per month or per year. As long as the unit is the same for the reservation wage and the previous wage, the specific choice of unit is irrelevant. When the units are not the same, we convert by assuming 40 hours per week and 4.3 weeks per month. In addition, we define the after tax earnings of the individual as $(1-\tau)$*Earnings, where $\tau = .25$ for everyone in the sample. This has the effect of understating the UI replacement ratio for high income individuals, and overstating it for low income (and tax rate) individuals.

Our second major variable is the unemployment benefit replacement rate. Respondents were asked whether they had received any unemployment insurance benefits during their current spell of unemployment; if they had, they were asked what their weekly benefit was. We use the ratio of this reported U.I. benefit to previous earnings as our measure of the replacement rate.[13]

Since data are not available on the amount of supplementary unemployment benefits, welfare, and other forms of nonwage income received by the unemployed, it is not possible to measure their specific effects on transition probabilities. Information is available, however, on whether or not the individual received welfare payments. We included a binary variable, which takes the value of 1 if welfare is received and zero otherwise, in the equations, and regard its coefficient as a weak indication of whether welfare income affects the probability of leaving unemployment.

Several other variables are also included in the logit specification. Indicator variables for the cause of unemployment, whether the individual was a job loser or a job leaver, and for central city residence are also among the explanatory variables. SMSACEN, the central city variable, is included to capture the lower search costs and higher probability of finding re-employment attendant with city residence. We also include demographic variables, such as race, marital status, and age-sex subcategory

---

[13]Our unemployment insurance variable refers to the amount of U.I. benefits actually received during the unemployment spell and not to the benefits to which the individual was entitled under the law. An individual may not receive U.I. benefits because (1) he is not eligible for benefits (having exhausted benefits or had insufficient previous work experience) or because (2) he has not yet applied for benefits or because (3) he has applied but has not yet received benefits because of administrative delays in the payment of U.I.

indicators, in all of our models.

Table 3 shows estimates of the basic multinomial transition model for the full sample. There are estimates of both unemployment transition and labor force withdrawal probabilities. Corresponding to each transition, three equations are reported. The first, or "No Error" model, assumes no measurement errors. This is the standard multinomial logit model for our problem. The second model, with "Error Probabilities A," uses reinterview survey error probability estimates from Table 1. Finally, we estimated several models using error probabilities from panel B in Table 1.

The results show both that the receipt of unemployment benefits has an important effect on transition probabilities and that correction for measurement errors can have substantial effects on the estimated coefficients. The U.I. variable has the predicted negative sign in the employment transition model, and it has an even larger, negative effect on the probability of leaving the labor force. This is presumably due to the "reporting effect", the requirement of on-going search as a precondition for UI receipt. The UI coefficient in the P_{UE} equation rises by twenty-five percent between the no-error and the error rate B models. The coefficient in the P_{UN} equation changes from -1.44 to -2.08, a move of forty-five percent.

The welfare variable takes its predicted sign in each equation, though it is statistically significant in only about one-half of the estimated equations. The coefficient also changes substantially when we estimate the model allowing for measurement error.

The demographic variables also have their predicted signs: married women are less likely to find jobs, and more likely to leave the labor force, than are married men. Job losers and job leavers both have lower probabilities of becoming reemployed than do other groups.

Finally, the reservation wage variable is a disappointment. While we would have predicted that a higher reservation wage-to-last-wage ratio would be linked to fewer acceptable job offers and therefore to longer expected spell durations, this is not supported by the data. The coefficients in the employment transition equation are always positive, although they are statistically insignificant. One argument often made in defense of search models is that they do not apply to individuals on temporary layoff, and therefore may appear inconsistent with the data findings. To test this view, we deleted the 76 temporary-layoff individuals in our sample and re-estimated the model. The results, which are reported in an earlier draft of this paper, are very similar to those for the full sample.

A more significant change in the specification is reflected in the models of Table 4. We included both the number of weeks reported to have elapsed in the current unemployment spell, and the number of hours per week which the individual reported spending each week on job search, in the transition equations. Both variables have substantial, and significant, effects in explaining the exit probabilities from unemployment. The coefficient on the duration variable is negative, indicating that the longer the spell of unemployment has lasted, the lower is the probability of re-employment.[14] The search intensity variables also behave as predicted, and higher search effort results in a higher job-finding probability.

The foregoing results display the substantial importance of accounting for classification errors in analyzing labor market transitions. Many of the estimated coefficients change by more than thirty percent when the model is estimated using the error probabilities estimated from the Reinterview Survey. When estimated with higher error probabilities, the findings show even more substantial changes.[15]

The inclusion of the duration and intensity variables reduces the U.I. coefficient in the employment transition equation by about sixty percent. This may indicate that one of the ways UI affects the probability of finding a job is by changing search intensity. Alternatively, UI receipt might just be capturing the fact that most UI recipients have relatively short spells, since eligibility usually expires at either 26 or 39 weeks. Inclusion of duration has almost no effect on the UI coefficient in the labor force withdrawal equations.

4. Interpretation and Conclusions

The estimated logit models may be used to determine the changes in

---

[14]From this information it is not possible to distinguish the hypotheses of heterogeneity (there are some workers who are very unlikely to become reemployed in any period, and who therefore experience long spells of unemployment) from that of state-dependence (being in the midst of a long unemployment spell actually reduces the probability of becoming re-employed).

[15]In some cases the coefficients seem to change by large, and implausible amounts. However, these parameter estimates are usually accompanied by large standard errors.

transition probabilities caused by unemployment insurance. In the usual case, say

(11)
$$P_{UE} = \frac{e^{-X_i\beta_1}}{1+e^{-X_i\beta_1}+e^{-X_i\beta_2}}$$

the derivative of a probability with respect to one of the X_j is

(12)
$$\frac{\partial P_{UE}}{\partial X_j} = -\beta_{1j}P_{UE}[1-P_{UE}-\frac{\beta_{2j}}{\beta_{1j}}P_{UN}].$$

In the more general case in which there are errors in classification, and we wish to know how the probability of <u>observing</u> a particular outcome will change, the calculation proceeds as follows:

(13)
$$\begin{aligned}\frac{\partial \bar{P}_{UE}}{\partial X_j} &= \frac{-(1-q_{EU}-q_{EN})\beta_{1j}e^{-X_i\beta_1}-q_{NE}\beta_{2j}e^{-X_i\beta_2}}{1+e^{-X_i\beta_1}+e^{-X_i\beta_2}} \\ &+ \frac{(\beta_{1j}e^{-X_i\beta_1}+\beta_{2j}e^{-X_i\beta_2})}{(1+e^{-X_i\beta_1}+e^{-X_i\beta_2})}\cdot\frac{(q_{UE}+(1-q_{EU}-q_{EN})e^{-X_i\beta_1}+q_{NE}e^{-X_i\beta_2})}{(1+e^{-X_i\beta_1}+e^{-X_i\beta_2})} \\ &= -\beta_{1j}P_{UE}\cdot\left[(1-q_{EU}-q_{EN})+\frac{\beta_{2j}}{\beta_{1j}}q_{NE}\frac{P_{UN}}{P_{UE}}-\tilde{P}_{UE}\left(1-\frac{\beta_{2j}}{\beta_{1j}}\cdot\frac{P_{UN}}{P_{UE}}\right)\right].\end{aligned}$$

The derivatives of probabilities of <u>observing</u> given outcomes are important if we wish to evaluate the change in the <u>measured</u> unemployment rate as a result of a policy reform.

The derivatives of probabilities with respect to changes in the level of U.I. benefits are shown in Table 5. The calculation proceeds for a "typical" individual, defined as someone with the sample average transition probabilities of P_{UE} = .233 and

P_{UN} = .048.[18] A change of .50 in the unemployment insurance replacement ratio, from 0 to .50, results in a -.10 change in the unemployed worker's probability of becoming employed in a given period and a -.054 change in P_{NE}.[17] The expected spell duration if there were no unemployment benefits, $1/(P_{UE} + P_{UN})$, would be 2.78 months. The introduction of UI which provides benefits equal to fifty percent of the worker's post tax wage increases the expected duration to 4.32 months. The sensitivity of the duration results is substantially greater in the case of the "errors adjusted" transition probabilities.

Note the important differences between the expected spell durations computed using the unadjusted transition probabilities and those adjusted for measurement error. The expected duration is nearly a month longer when computed using transition probabilities that are not contaminated by spurious transitions due to reporting error.

---

[18]The true transition probabilities for the "sample average" individual are calculated by solving the system of linear equations in (6).

$$\tilde{P}_{UE} = \frac{234}{908} = .257 = q_{EE}P_{UE}+q_{UE}P_{UU}+q_{NE}P_{UN}$$

$$\tilde{P}_{UU} = \frac{561}{908} = .619 = q_{EU}P_{UE}+q_{UU}P_{UU}+q_{NU}P_{UN}$$

$$\tilde{P}_{UN} = \frac{110}{908} = .124 = q_{EN}P_{UE}+q_{UN}P_{UU}+q_{NN}P_{UN}$$

for P_{UE}, P_{UU}, and P_{UN}, using the Reinterview $[q_{ij}]$ and the knowledge that 234 of the 908 people in our sample became employed and 110 left the labor force. This yields P_{UE} = .233, P_{UU} = .719, and P_{UN} = .048.

[17]Calculations performed using parameter estimates from the "No Error" and "Error Specification B" in Table 3.

This finding sheds important light on the "dynamics of unemployment" controversy, since it shows that using unadjusted transition probabilities leads to estimated spell durations which are biased downward by a substantial amount.

This paper has confronted the problem of response errors in the Current Population Survey and developed a procedure for analyzing survey data under particular circumstances: when one of the observations in a panel is measured without error. A natural avenue for extension is to allow both (or all) observations in a panel to be subject to measurement error. Fuller (1987) discusses a number of models for analyzing data that is measured with error; some of these models could be applied to labor market data. Krueger and Summers (1988) describe methods for treating measurement error in indicator variable data. The current approach might also be integrated with the various procedures that have recently been developed for analyzing life and duration data. Our analysis also suggests ways to assess the robustness of empirical findings to the possibility of measurement error in the labor market data.

References

Atkinson, A. and J. Micklewright (1991). "Unemployment Compensation and Labor Market Transitions: A Critical Review," Journal of Economic Literature 29 (December), 1679-1727.

Baron, J.M. and W. Mellow (1981). "Changes in Labor Force Status Among the Unemployed," Journal of Human Resources 16, 427-42.

Biemer, Paul P., and Gosta Forsman (1992). "On the Quality of Reinterview Data with Application to the Current Population Survey," Journal of the American Statistical Association 87, 915-923.

Bound, John, Charles Brown, Greg Duncan, and Willard Rodgers (1990). "Measurement Error in Cross-Sectional and Longitudinal Labor Market Surveys: Validation Study Evidence," in J. Hartog, G. Ridder, & J. Theeuwes, eds., Panel Data and Labor Market Studies (Amsterdam: Elsevier Science Publishers), 1-19.

Bound, John and Alan B. Krueger (1991). "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?," Journal of Labor Economics 9 (January), 1-24.

Bureau of the Census (1963). The Current Population Survey Reinterview Program: January 1961 through December 1966. Technical Paper No. 19 (Washington, D.C.: Government Printing Office).

Clark, Kim B. and Lawrence H. Summers (1979). "Labor Market Dynamics and Unemployment: A Reconsideration," Brookings Papers on Economic Activity 1:1979, 13-60.

Duncan, Greg and Daniel Hill (1985). "An Investigation of the Extent and Consequences of Measurement Error in Labor-Economic Survey Data," Journal of Labor Economics 3, 508-532.

Feldstein, Martin S. and James M. Poterba (1984). "Unemployment Insurance and Reservation Wages," Journal of Public Economics 23, 141-169.

_________ (1982). "Models for the Analysis of Labor Force Dynamics," in R. Bassmann and G. Rhodes, eds., Advances in Econometrics. Greenwich, Conn.: JAI Press.

Flinn, C.J. and J.J. Heckman (1983). "Are Unemployment and Out of the Labor Force Behaviorally Distinct States," Journal of Labor Economics 1 (January), 28-42.

Fuller, Wayne (1987). Measurement Error Models. New York: John Wiley & Sons, Inc.

Graham, Dorcas W. (1974). "Estimation, Interpretation, and Use of Response Error Measurements," unpublished paper, U.S. Commerce Department.

Krueger, Alan B., and Lawrence H. Summers (1988). "Efficiency Wages and the Inter-Industry Wage Structure," Econometrica 56 (March), 259-294.

Lancaster, T. (1979). "Econometric Models for the Duration of Unemployment," Econometrica 47, 939-956.

Lippman, S. and J. McCall (1976). "The Economics of Job Search," Economic Inquiry 14, 155-189.

Poterba, James M. and Lawrence H. Summers (1984). "Response Variation in the CPS: Caveats for Unemployment Analysts," Monthly Labor Review (March), 37-43.

_______ (1986). "Reporting Errors and Labor Market Dynamics," Econometrica 54 (November), 1319-1338.

Rosenfeld, Carl (1977). "Job Search of the Unemployed, May 1976," Monthly Labor Review, vol. 100 (November), 39-47.

Woltman, Henry and Irv Shreiner (1979). "Possible Effects of Response Variance on the Gross Changes Data," unpublished Bureau of Census memo, May 11.

TABLE 1

Misclassification Probabilities

Error Matrix A: Calculated Re-interview Error Probabilities

True State	Recorded State		
	Employed	Unemployed	NILF
Employed	.9905	.0016	.0079
Unemployed	.0356	.8602	.1041
NILF	.0053	.0025	.9923
		N = 7079	

Error Matrix B: Alternative Error Probabilities

True State	Recorded State		
	Employed	Unemployed	NILF
Employed	.950	.040	.010
Unemployed	.070	.720	.210
NILF	.020	.180	.800

Source: Error Matrix A was computed from a table of "General Labor Force Status in the CPS Reinterview By Labor Force Status in the Original Interview, Both Sexes, Total, After Reconciliation," May 1976, provided from unpublished records at the Census Department. Error Matrix B was constructed by the authors to illustrate a plausible scenario for measurement errors in unemployment transition studies.

Table 2

Disaggregated Misclassification Probabilities

Calculated Re-interview Error Probabilities (Men)

True State	Recorded State Employed	Unemployed	NILF
Employed	.9922	.0013	.0065
Unemployed	.0474	.8720	.0806
NILF	.0062	.0048	.9890
		N = 3329	

Calculated Re-interview Error Probabilities (Women)

True State	Recorded State Employed	Unemployed	NILF
Employed	.9892	.0019	.0089
Unemployed	.0194	.8442	.1363
NILF	.0049	.0015	.9936
		N = 3750	

Source: Computed from a table of "General Labor Force Status in the CPS Reinterview By Labor Force Status in the Original Interview, Both Sexes, Total, After Reconciliation," May, 1976, provided from unpublished records at the Census Department.

TABLE 3

Logit Transition Model Estimates

Variable	Employment Transition			NILF Transition		
		Error Probabilities			Error Probabilities	
	No Error Model	A	B	No Error Model	A	B
Constant	-.678 (.729)	-.762 (.675)	-.481 (1.126)	+.075 (.567)	+.122 (.736)	+.657 (1.633)
Job Loser	-.379 (.547)	-.413 (.208)	-.459 (.242)	-.551 (.852)	-1.483 (.527)	-4.131 (2.000)
Job Leaver	-.189 (.732)	-.134 (.260)	-.132 (.303)	-.603 (.945)	-.768 (.541)	-15.51 (6.263)
UI Ratio	-1.146 (1.268)	-1.189 (.513)	-1.428 (.606)	-1.915 (1.304)	-1.859 (1.213)	-2.761 (3.350)
RW Ratio	+.107 (.377)	+.147 (.146)	+.159 (.173)	-.072 (.615)	-.017 (.258)	-.399 (.561)
Welfare (1=Recipient)	-.278 (.917)	-.435 (.353)	-.622 (.440)	+1.381 (.958)	+2.741 (.739)	+1.950 (15.940)
SMSACEN	-.254 (.398)	-.335 (.187)	-.425 (.212)	+.139 (.730)	+.178 (.392)	+1.451 (1.124)
Race (1=Non-white)	-.019 (.959)	+.034 (.247)	+.046 (.291)	-.588 (.989)	-1.895 (.952)	-6.577 (2.705)
Single Man	+.609 (.655)	+.594 (.661)	+.460 (1.121)	-1.333 (.930)	-14.419 (39.18)	-62.302 (31.818)
Married Man	+.471 (.616)	+.425 (.649)	+.176 (1.104)	-2.360 (.944)	-12.722 (39.281)	-40.941 (18.568)
Married Woman	-.103 (.753)	-.259 (.303)	-.435 (.356)	+.969 (.780)	+1.391 (.563)	26.903 (14.891)
Log Likelihood	-758.78	-758.47	-787.13	-758.78	-758.47	-787.13

Notes: Standard errors are shown in parentheses. Sample size is N = 908, of which 234 display transitions to employment, and 113 transit to NILF.

TABLE 4
Logit Transition Model Estimates Including Spell Duration

	Employment Transition Equation		NIL Transition Equation	
Variable	No Error Model	Error Matrix A	No Error Model	Error Matrix A
Constant	-.137 (.963)	-.120 (.857)	+.572 (.840)	+.784 (.914)
Job Loser	-.308 (.258)	-.323 (.219)	-.580 (.314)	-1.549 (.574)
Job Leaver	-.193 (.299)	-.237 (.293)	-.478 (.362)	-.769 (.566)
UI Ratio	-.534 (1.014)	-.393 (.509)	-1.712 (1.113)	-1.361 (1.115)
RW Ratio	+.041 (.195)	+.047 (.155)	-.087 (.084)	-.038 (.301)
Welfare (1 = Recipient)	-.116 (.504)	-.138 (.367)	+1.380 (.441)	+3.171 (.777)
SMSACEN	-.277 (.197)	-.307 (.203)	+.215 (.325)	+.049 (.422)
Race (1 = Non-white)	-.106 (-.276)	-.114 (.267)	-.723 (.380)	-2.462 (.996)
Single Man	-.241 (.940)	+.096 (.852)	-1.650 (.801)	-11.351 (7.303)
Married Man	-.056 (.905)	-.163 (.840)	-2.591 (.631)	-95.21 (7.03)
Married Woman	-.113 (.542)	-.195 (.531)	+.976 (.266)	+1.77 (.561)
Weeks Unemployed	-.022 (.002)	+.029 (.006)	-.006 (.010)	-.019 (.015)
Hours/Wk Searching	+.018 (.009)	+.019 (.009)	-.009 (.019)	-.039 (.037)
Log Likelihood	-692.61	-689.70	-692.61	-689.70

Notes: Standard errors are shown in parentheses. The sample size is 843, of which 214 individuals report transitions to employment and 107 transit to NILF.

TABLE 5

Unemployment Spell Durations and U.I.

Concept	Without reporting error correction	With reporting error correction
Probability of Becoming Employed		
— Actual (P_{UE})	.257	.233
— Observed ($\tilde{P}_{UE}$)	.257	.257
Probability of Labor Force Withdrawal		
— Actual (P_{UN})	.124	.048
— Observed ($\tilde{P}_{UN}$)	.124	.124
Expected Actual Spell Duration ($1/(P_{UN} + P_{UE})$)	2.62 months	3.55 months
Expected Duration of Observed Spells ($1/(\tilde{P}_{UN} + \tilde{P}_{UE})$)	2.62 months	2.62 months
"Indomitable Worker" Expected Spell Duration ($1/P_{UE}$)	3.89 months	4.29 months
$\partial P_{UE}/\partial$(UI replacement ratio)	-.157	-.191
$\partial \tilde{P}_{UN}/\partial$(UI replacement ratio)	-.157	-.215
$\partial P_{UN}/\partial$(UI replacement rate)	-.171	-.052
$\partial \tilde{P}_{UN}/\partial$(UI replacement rate)	-.171	-.109
∂(Expected Duration) /∂(UI Replacement ratio)	2.25	3.06
Expected Duration (UI = 0)*	2.06 months	2.78 months
Expected Duration (UI = .5)*	3.18 months	4.32 months

Source: Authors' calculations based on the "no error" and "Error A" equations in Table 3. * = calculation based on average UI replacement ratio of .24 implicit in aggregate transition probabilities for the sample.