THE INFORMATION CONTENT IN THE DISTINCTION BETWEEN UNEMPLOYMENT AND OUT OF THE LABOR FORCE STATUSES FOR MARRIED WOMEN

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December 1997

*The authors gratefully acknowledge research support from Arizona State University's Business Dean's Council of 100. We also appreciate comments from Paul Burgess on an earlier draft of this paper.
1. INTRODUCTION

Labor supply decisions can be considered a joint outcome of two distinct choices: The initial choice may be characterized as an individual’s preference to work or the labor force participation decision. Given entry into the labor force, the second choice reflects the ability to find a job prospect with wage offer exceeding the reservation wage. Identification and estimation of these two processes are important for the correct measurement of labor force participation and unemployment rates. Labor statistics estimate these two measures by categorizing individuals into three distinct labor market statuses: out of the labor force (OLF) individuals, who choose not to enter the labor force; unemployed (UN) individuals, who enter the labor force but are unsuccessful in obtaining a satisfactory offer; and employed (EMP) individuals, who enter the labor force and receive a satisfactory offer. Although neither OLF nor UN individuals are working, labor statistics distinguish between them by including UN (as well as EMP) in measures of the labor force. An implicit assumption behind this distinction is that UN individuals will work if acceptable jobs are offered, while OLF individuals prefer not to work.

The distinction between OLF and UN is important not only for accurately measuring the unemployment rate, but also for modeling labor force decisions and employment outcomes. In early studies of labor supply, unemployment is considered a voluntary phenomenon. Only the labor force entry decision is relevant for employment, as an individual’s employment outcome is not constrained by the ability to find a job. In this formulation OLF and UN are treated as behaviorally equivalent statuses (Heckman, 1974 and Hausman, 1980). In contrast, recent studies explicitly distinguish between the two states by treating the labor force participation decision and the ability to find a job as distinct choices. This alternative formulation is consistent with the
classification of three separate labor force statuses. Separation of the three groups leads to identification of the differential effects of demographic or economic variables on labor force participation and employment probabilities (Blundell and Meghir, 1987, and Blundell, Ham and Meghir, 1987, 1995).\(^1\)

Although the theoretical distinction between OLF and UN is intuitively straightforward, whether or not to empirically consider two (EMP, not EMP) or three (EMP, UN, OLF) classifications in labor supply studies is a controversial issue. In this paper, we address this issue by estimating separate index functions for the labor force entry decision and the ability to receive an acceptable job offer outcomes. Our particular concern is the potential classification errors which may exist between OLF and UN individuals which may cloud inferences based on labor force classifications. If sizeable proportions of UN or OLF workers are misclassified, these errors will result in biased estimates of the two index functions and incorrect estimates of labor force participation and unemployment rates as well as inappropriate inferences relative to labor supply issues.

Search theory stipulates that the major difference between OLF and UN states relates to job search activity, with OLF individuals engaging in zero quantity and UN individuals pursuing a positive amount (Burdett and Mortensen, 1980 and Devine and Kiefer, 1991). From this foundation, the Bureau of Labor Statistics (BLS) has quite detailed specifications for classification, defining the unemployed as those who are available for a job during the reference week and have actively looked for a job during the preceding four weeks using at least one of a

\(^1\)Ahn (1990) and Sundt (1991) also estimate the labor force participation and employment equations by distinguishing the three labor market statuses. See also Bowlus (1995).
specified list of methods.\textsuperscript{2}

However, the BLS classification of OLF and UN cohorts may fail to correctly reveal nonworking individuals' preferences to work for several reasons. First, job search activity alone may not be a sufficient criterion by which nonworking individuals who prefer to work can be differentiated from those who prefer not to work. In the U.S., the average monthly flow to EMP from OLF is greater than the average flow to EMP from UN. \textbf{[Min: do we need a citation here?] This may indicate that a nonnegligible portion of OLF individuals are in fact available for employment, but are classified as OLF because of their low search intensity.}\textsuperscript{3} Second, all search information is self-reported and not independently verified. Thus responses are likely to be influenced by the form of the question.\textsuperscript{4} Third, some individuals, particularly those seeking to qualify for or continue to receive unemployment insurance benefits may have an incentive to over-report their search activity (Burgess, 1992). Finally, even if there were no reporting errors, the official BLS classification criteria lack concrete thresholds for the quantity of and intensity of the minimally required search activity needed for an individual to be classified as UN, leaving this determination to the discretion of the interviewer.\textsuperscript{5} For these reasons, one might expect the

\begin{itemize}
  \item \textsuperscript{2}Additionally included in UN are temporarily laid off workers and those waiting to report to a new job within a month.
  \item \textsuperscript{3}A nonworking individual preferring employment may not engage in job search if the job arrival rate for non-job-searchers is nonzero and search costs are high.
  \item \textsuperscript{4}An example of the potential impact of the form of survey questions is found in Filer, Hamermesh and Rees (1996, p. 7). In 1994 the Current Population Survey officially changed some questions related to female job search. Estimated unemployment rates based on the old vs. new questions differed by 0.8 percent.
  \item \textsuperscript{5}Estimated transitions from OLF to UN or vice versa are non-negligible and may exceed transitions to employment (Gönül, 1992; Flaim and Hogue, 1985). These results may suggest that many nonworking individuals are erroneously classified based on misreported search activity or
\end{itemize}
distinction between UN and OLF to be imprecise, with some individuals observationally equivalent to those who are UN (OLF) classified as OLF (UN). Thus use of BLS criteria may produce only an arbitrary distinction between UN and OLF (Clark and Summers, 1982).

Previous empirical consideration of whether OLF and UN are observationally identical or distinct has relied on an examination of labor market outcomes of the groups. Clark and Summers (1982) conclude that there is no distinction between the states based on identical mean durations of UN. Flinn and Heckman (1982) and Gönül (1992) view transition probabilities to employment, with Flinn and Heckman concluding that OLF and UN are distinct for young men, while Gönül finds a distinction for young women but not for young men. These tests thus do not provide uniform inferences. Further, by assuming that OLF and UN states are correctly identified, these studies may yield misleading inferences relative to unemployment rate estimates if there exists imprecision in the classification process.

In this paper, we consider an empirical specification (likelihood function) by which researchers can identify and estimate both the labor force participation and employment index functions using cross sectional data, even in the presence of potential classification errors between OLF and UN individuals. The contribution of our general specification is twofold. First, it provides simple parametric tests for the empirical distinction between the two nonworking groups in terms of their demographic and economic attributes. Second, the specification framework allows researchers to estimate the empirical lack of distinctness between individuals classified as

\[\text{interviewer error.}\]

\[6\text{Clark and Summers utilize Current Population Survey data for teenagers.}\]

\[7\text{Both Heckman and Flinn and Gönül use National Longitudinal Survey data for young people.}\]
UN or OLF. At one extreme, we may find no ambiguity of classification. Alternately, we may find classification imprecision in the UN classification (some UN individuals may have attributes more closely associated with OLF), in the OLF classification or in both. As the degree of estimated empirical ambiguity of classification rises, our ability to determine the distinctness of UN and OLF is diminished. Further, unemployment rates estimated assuming all classifications are accurate may be well off the mark. Our estimates will allow us to determine the degree of classification ambiguity and will provide us with revised estimates of unemployment and OLF rates accounting for the classification uncertainty.

We apply our empirical specification to a sample of married women obtained from the 1988 Panel Study of Income Dynamics. We find that the sample separation of OLF and UN individuals is useful to identify labor force participation and employment success decisions, although our results are consistent with the presence of classification errors between OLF and UN. We also find that estimates that ignore the possible classification errors are biased and underpredict both labor force entry and unemployment probabilities.

This paper is organized as follows. Section 2 set ups our basic model and discusses estimation procedures. Section 3 explains the sample used in our empirical study, and section 4 discusses our empirical results. Concluding remarks follow in section 5.

2. MODEL

In this section, we introduce a simple three-state model in which individuals' labor market statuses are distinguished based on two separate decisions. For this model, we derive a likelihood function which is designed to control for potential classification errors among OLF and UN individuals.
We also discuss the hypotheses of interest and model specification tests.

2.1 Basic Model

The foundation of our approach is a simple three-state model based on search theory, which is also considered by Blundell, Ham and Meghir (1995). We begin by assuming that jobs are not always available for individuals considering employment. Each worker is assumed to be aware of the probability that she can receive an acceptable job offer as well as the wage offer distribution and search costs, and then compares the expected value of job search to the value of her leisure and home production before she begins to look for a job. A woman becomes available for work and spends non-zero time on job search only if the former value exceeds the latter. With these assumptions, we define a married woman’s disposition to be in the labor force by the index function:

$$ y_{if}^* = X_{if} \beta_{if} + e_{if} . $$

(1)

Here $X_{if}$ contains explanatory variables relevant for labor force participation decisions, $\beta_{if}$ is a vector of their coefficients and $e_{if}$ is the random error term. The latent variable $y_{if}^*$ can be viewed as the difference between the expected value of job search and the value of OLF activity.

Given an individual’s participation, the likelihood of her being employed depends both

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8See also Ahn (1990) and Sundt (1991).

9 For a rigorous theoretical derivation of this labor force participation rule, see Blundell, Ham and Meghir (1995). The value of search also depends on the probability of separation from jobs (e.g., lay offs).

10 Here and later, we drop subscript "i" indexing individuals for notational convenience.
upon job-search intensity and effectiveness as well as on labor demand. In order to capture this probability, we define the employment index function by:

\[ y_{emp}^* = X_{emp} \beta_{emp} + e_{emp}, \]

(2)

where all the terms are defined similarly to those in equation (1). Here the latent variable \( y_{emp}^* \) measures job availability. We assume that given her participation decision, a woman is employed whenever \( y_{emp}^* > 0 \), and otherwise remains unemployed.

Two points made by Blundell, Ham and Meghir (1995) are worth noting for the proper interpretation of the employment index function. First, the probability of positive employment, \( \Pr(y_{emp}^* > 0) \), does not simply coincide with the job arrival rate. Since laid-off workers are also included as unemployed in the data, this probability can be interpreted as the sum of the arrival rate for job searchers and the job-retention rate for employed workers. Second, since employment probability affects labor force decisions through the value of search, and since all the variables relevant for labor force decisions would also likely affect the employment probability through the reservation wage and search intensity, it is unlikely that different variables influence labor force participation and employment probabilities. Accordingly, we specify \( X_{lf} = X_{emp} = X \).

In addition, we assume that the employment function (2) is an unconditional one defined for all individuals regardless of their participation decisions. Therefore, the positive sign of \( y_{emp}^* \) for an OLF individual should be interpreted as meaning that an acceptable job would be available to her if she decided to participate in the labor force.

A woman's latent true EMP, UN and OLF states (which we denote by TEMP, TUN and TOLF, respectively) depend on the signs of the latent variables \( y_{lf}^* \) and \( y_{emp}^* \). Specifically, if we assume that the error terms \( e_{lf} \) and \( e_{emp} \) follow a bivariate standard normal distribution, the
probability of being in one of the three states is given by:

\[ Pr(i \in TEMP) = Pr(y^*_{lf} > 0 \text{ and } y^*_{emp} > 0) = F(X\beta_{lf}, X\beta_{emp}, \rho); \]

\[ Pr(i \in TUN) = Pr(y^*_{lf} > 0 \text{ and } y^*_{emp} < 0) = \Phi(X\beta_{lf}) - F(X\beta_{lf}, X\beta_{emp}, \rho); \]

\[ Pr(i \in TOLF) = Pr(y^*_{lf} < 0) = 1 - \Phi(X\beta_{lf}); \]

where \( F(\cdot, \cdot, \cdot) \) and \( \Phi(\cdot) \) represents bivariate and single standard normal cumulative density functions, respectively, and \( \rho \) is the correlation coefficient between \( e_{lf} \) and \( e_{emp} \). Therefore, given an individual's demographic and economic attributes \( X \), these three probabilities can be explained by the parameter vector \( \theta = (\beta_{lf}', \beta_{emp}', \rho)' \).\(^{11}\)

### 2.2. Model with Classification Errors

Identification and estimation of the model given by equations (1) and (2) requires a sample classification of individuals into EMP, UN and OLF groups. We denote the classified labor market states of the women in our sample by CEMP, CUN and COLF, respectively. In cases where these observed states coincide with true states, equations (1) and (2) can be viewed as a bivariate probit model with partial observability (see Meng and Schmidt, 1985). In particular, since employment outcomes are observable only for labor force participants, the model corresponds to the censored probit case (Farber, 1983), which leads to the log-likelihood function:\(^{12}\)

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\(^{11}\) If we restrict \( \rho = 0 \), the employment equation (2) may be regarded as a conditional one defined over LF participants only. In this case, the parameters in equations (1) and (2) can be estimated by two separate probits.

\(^{12}\) As classified and true states are here assumed at this point to be identical, \( Pr(i \in TOLF) = Pr(i \in COLF) \) with comparable equivalencies for UN and EMP. For later clarity, we express
\[
I_c(\theta) = \sum_{i \in \text{CEMP}} \ln \Pr(i \in \text{CEMP}) + \sum_{i \in \text{CUN}} \ln \Pr(i \in \text{CUN}) + \sum_{i \in \text{COLF}} \ln \Pr(i \in \text{COLF})
\]
\[
= \sum_{i \in \text{CEMP}} \ln F(X\beta_{lf}, X\beta_{emp}, \rho) + \sum_{i \in \text{CUN}} \ln [\Phi(X\beta_{lf}) - F(X\beta_{lf}, X\beta_{emp}, \rho)] \]
\[
+ \sum_{i \in \text{COLF}} \ln [1 - \Phi(X\beta_{lf})].
\]

Consistency of the censored probit (maximum likelihood) estimates crucially depends on whether the sample distinction between CUN and COLF is relevant. When this distinction is questioned, for the reasons mentioned in the previous section, one may wish to estimate equations (1) and (2) without distinguishing the two states. This scenario leads to an alternative estimation procedure that is considered by Poirier (1980). Using Poirier’s method we need only distinguish employed and nonemployed (both CUN and COLF) women. Under this formulation the relevant log-likelihood function is given by:

\[
I_p(\theta) = \sum_{i \in \text{CEMP}} \ln \Pr(i \in \text{CEMP}) + \sum_{i \in \text{CEMP}} \ln \Pr(i \notin \text{CEMP})
\]
\[
= \sum_{i \in \text{CEMP}} \ln F(X\beta_{lf}, X\beta_{emp}, \rho) + \sum_{i \notin \text{CEMP}} \ln [1 - F(X\beta_{lf}, X\beta_{emp}, \rho)].
\]

Given that observed employment and nonemployment statuses do not contain classification errors, maximizing the log-likelihood function (5) can yield a consistent estimator of the true values of \( \theta \).

However, a serious limitation in the Poirier method is that the parameter vectors \( \beta_{lf} \) and \( \beta_{emp} \) are not identified because of their interchangability in equation (5). That is, although it is possible to estimate the two parameter vectors by maximizing \( I_p(\theta) \), it is not possible to determine which estimates are for which equation unless some prior information is available on different

the likelihood function in terms of CEMP, CUN and COLF.
effects a variable may have (in terms of sign or size) on participation decisions and employment outcomes, or unless \( X_{ij} \) and \( X_{emp} \) are distinct, which is a restriction that may be difficult to justify in practice.

A method we adopt to circumvent this identification problem is to generalize the censored probit model in (4) by parameterizing the probabilities of discrepancies between observed and true nonemployment statuses UN and OLF. Specifically, we define:

\[
\begin{align*}
P_1 &= P(r(i \in CUN| i \in TUN) = \Phi(Z_1 \gamma_1) ; \\
P_2 &= P(r(i \in CUN| i \in TOLF) = \Phi(Z_2 \gamma_2) ,
\end{align*}
\]

where \( Z_1 \) and \( Z_2 \) denote vectors of explanatory variables, and \( \gamma_1 \) and \( \gamma_2 \) are corresponding coefficients. Here \( P_1 \) represents the conditional probability that an individual’s reported UN status (CUN) coincides with her true UN status (TUN), while \( 1 - P_1 \) represents the probability that an UN individual is misclassified as OLF. The conditional probability \( P_2 \) represents the probability that an OLF individual is misclassified as UN, while \( 1 - P_2 \) is the probability that her reported OLF status is correctly reported. Since both \( P_1 \) and \( P_2 \) are defined as conditional on true unemployed or true OLF status, they are likely to be related to all the explanatory variables for the labor force participation decision and ability to find a job outcome equations. Therefore, we simply specify \( Z_1 = Z_2 = X \).

The conditional probability \( P_1 \) can be also interpreted as a measure of the unambiguity of reported UN individuals' true status in terms of their demographic and economic attributes \( X \). For example, if \( P_1 \) equals to one for all nonworkers, this implies that all nonworkers with characteristics consistent with UN (TUN) are classified as UN (CUN). If \( P_1 \) is less than one, it

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\(^{13}\)Since this specification is somewhat arbitrary, its validity is subject to some justifying specification tests, which we discuss below.
indicates that some nonworkers with characteristics consistent with UN (TUN) are misclassified as OLF (COLF). In contrast to $P_1$, the conditional probability $P_2$ measures the degree of ambiguity of observed OLF individuals. That is, if $P_2$ equals zero, all nonworkers with OLF attributes (TOLF) are classified as OLF (COLF). However, when $P_2$ is greater than zero, it indicates that some nonworkers having attributes consistent with OLF (TOLF) are misclassified as UN (CUN).

We may now specify a generalized censored model, which is used for our empirical study. Introducing the two conditional probabilities $P_1$ and $P_2$, we can define the unconditional probabilities of being in CUN and COLF as:

\[
Pr(i \in \text{CUN}) = Pr(i \in \text{CUN}|i \in \text{TUN})Pr(i \in \text{TUN}) + Pr(i \in \text{CUN}|i \in \text{TOLF})Pr(i \in \text{TOLF})
\]

\[
= \Phi(X\gamma_1)[\Phi(X\beta_y) - F(X\beta_y, X\beta_{emp}, \rho)] + \Phi(X\gamma_2)[1 - \Phi(X\beta_y)];
\]

\[
Pr(i \in \text{COLF}) = Pr(i \in \text{COLF}|i \in \text{TUN})Pr(i \in \text{TUN}) + Pr(i \in \text{COLF}|i \in \text{TOLF})Pr(i \in \text{TOLF})
\]

\[
= [1 - \Phi(X\gamma_1)][\Phi(X\beta_y) - F(X\beta_y, X\beta_{emp}, \rho)] + [1 - \Phi(X\gamma_2)][1 - \Phi(X\beta_y)].
\]

If we insert equations (7) and (8) into equation (4), we obtain the following log-likelihood function for the generalized censored probit specification:

\[
l_g(\theta, \gamma) = \sum_{i \in \text{EMP}} \ln F(X\beta_y, X\beta_{emp}, \rho)
\]

\[
+ \sum_{i \in \text{CUN}} \ln \{\Phi(X\gamma_1)[\Phi(X\beta_y) - F(X\beta_y, X\beta_{emp}, \rho)] + \Phi(X\gamma_2)[1 - \Phi(X\beta_y)]\}
\]

\[
+ \sum_{i \in \text{COLF}} \ln \{[1 - \Phi(X\gamma_1)][\Phi(X\beta_y) - F(X\beta_y, X\beta_{emp}, \rho)] + [1 - \Phi(X\gamma_2)][1 - \Phi(X\beta_y)]\},
\]

where $\theta = (\beta, \rho)'$ and $\gamma = (\gamma_1, \gamma_2)'$. It can be easily shown that all the parameters in equation (9) can be identified unless $\gamma_1 = \gamma_2$.

\[14\]It would also be possible to specify the likelihood function to include the probability of classification errors in reported EMP status. However, as this is an observable event, we presume
The generalized censored probit model (9) directly nests both the censored and Poirier probit models (4) and (5) and will thus permit specification tests of the appropriateness of either specification. Specifically, the censored probit model (4) is obtained if $\Phi(X\gamma_1) = 1$ and $\Phi(X\gamma_2) = 0$ for all nonworking individuals. This occurs when there are no classification errors for either unemployed or OLF individuals, and implies that CUN and COLF coincide with TUN and TOLF, respectively. Accordingly, the presence of misclassified UN and OLF statuses in our sample can be easily checked by conventional likelihood-ratio (LR), Lagrange-Multiplier (LM) or Wald tests of the hypothesis that $\Phi(X\gamma_1) = 1 - \Phi(X\gamma_2) = 1$.

On the other hand, if $\Phi(X\gamma_1) = \Phi(X\gamma_2)$ for all nonworkers ($\gamma_1 = \gamma_2$ or equivalently $P_1 = P_2$) the likelihood function (9) reduces to:

$$l_p(\theta) + \left\{ \sum_{i \in \text{CUN}} \ln[\Phi(X\gamma_1)] + \sum_{i \in \text{COLF}} \ln[1 - \Phi(X\gamma_1)] \right\}.$$  

(10)

and provides estimates of $\theta$ that are equivalent to the Poirier probit estimates of $\theta$ from equation (5).

15 Testing the Poirier specification (5) against the generalized censored probit model (9) is equivalent to testing the information content of the distinction between reported UN and OLF (CUN and COLF). When $\gamma_1 = \gamma_2$ the general censored probit and Poirier models are informationally equivalent in terms of estimation of $\beta_{\text{lf}}$ and $\beta_{\text{emp}}$, and the distinction between CUN and COLF provides no information for the separate identification of labor force and employment decisions. 16 In contrast, if $\gamma_1 \neq \gamma_2$, the parameters $\beta_{\text{lf}}$ and $\beta_{\text{emp}}$ are no longer interchangeable and

CEMP = TEMP.

15This occurs because the second term of equation (10) is irrelevant for the estimation of $\theta$ as it contains only $\gamma_1$ ($= \gamma_2$).

16This occurs because $\beta_{\text{lf}}$ and $\beta_{\text{emp}}$ are interchangeable in equation (9) if $\gamma_1 = \gamma_2$.  

12
labor force and employment decisions can be separately identified. This implies that whether or not the distinction between CUN and COLF is informative for individuals' labor force and employment decisions can be checked by parametric tests of the relevance of the restriction $\gamma_1 = \gamma_2$.

Several intermediate outcomes warrant discussion. If $P_1$ is less than one and $P_2$ equals zero, the sole ambiguity of classification arises as some individuals observationally equivalent to those who are TUN are classified as OLF. Conversely, if $P_2$ is greater than zero and $P_1$ equals one, some individuals observationally equivalent to those who are TOLF are classified as UN, with no ambiguity of classification for those individuals with UN characteristics. Finally, if $P_1$ is less than one and $P_2$ is greater than zero (and are unequal) we would have dual classification ambiguity. In each of these intermediate cases, we might reject both the censored probit and Poirier probit representations of the labor force. Our results would indicate that distinguishing three labor force statuses (OLF, UN and EMP) is appropriate, but failure to consider the ambiguity of classification may provide misleading inferences. In addition, any of the intermediate cases has implications for estimated UN and OLF proportions. In the first case, unemployment rate estimates would be overstated; in the second case, unemployment rate estimates would be understated; while in the third case, unemployment estimates could be over or understated depending on the magnitude of the classification overlap.

### 2.3. Specification Tests

The reliability of statistical inferences based on the generalized censored probit model (9) is critically dependent on the correct specification of the model. Several specification tests will be
utilized to test the null hypothesis that the general model is correctly specified. We utilize both a Hausman (1978) test statistic:

\[ HT_g = (\hat{\theta}_p - \hat{\theta}_g)[V(\hat{\theta}_p - \hat{\theta}_g)]^{-1}(\hat{\theta}_p - \hat{\theta}_g) \sim \chi^2(q) \]  \hspace{1cm} (11)

and a Hausman score test (following Peters and Smith, 1991):

\[ HST_g = s_p(\hat{\theta}_g)[V[s_p(\hat{\theta}_g)]]^{-1}s_p(\hat{\theta}_g) - \chi^2(q) \]  \hspace{1cm} (12)

to perform our specification tests. In equations (11) and (12), \( \hat{\theta}_p \) and \( \hat{\theta}_g \) denote parameter estimates from the Poirier and generalized censored probit models, respectively; \( s_p(\theta) = \partial l_p(\theta)/\partial \theta \) represents a score vector; \( V(\bullet) \) captures the relevant variance-covariance matrix and \( q \) equals the number of parameters in \( \theta \). The Appendix to this paper contains the derivations of the \( HT_g \) and \( HST_g \) test statistics as well as a description of how the variance-covariance matrices may be consistently estimated.
3. DATA AND VARIABLES

We estimate the generalized censored probit model (9) using a sample of married women from the 1988 Panel Study of Income Dynamics (PSID). The initial potential sample of 4,048 women is reduced to 2,706 observations by several data exclusions.\(^{17}\) Definitions of the variables used in our estimation along with sample means and standard deviations are presented in Table 1. 73.8% of our sample is in the labor force, with the remaining 26.2% classified as OLF, with many of these individuals reporting their status as housewives. For the full sample, 69.5% are employed, implying that 4.3% are UN.\(^{18}\) These UN women are so classified because they have been looking for jobs during the last four weeks or are temporarily laid-off.

Other variables in Table 1 are explanatory variables included to capture the woman’s disposition to enter the labor force and ability to find an acceptable job. As noted above, provided the two conditional probabilities \(P_1\) and \(P_2\) are not equal, our generalized censored probit model permits identification of both LF and EMP equations (along with \(P_1\) and \(P_2\)) with identical sets of covariates. We thus include all explanatory variables in both equations and avoid a difficult to theoretically justify distinction between regressors included in each equation. Demographic effects on both labor force and employment decisions are captured by using variables such as dummy variables for high school and college diplomas (HSGRAD and COGRAD), the numbers of children below the ages of 6 and 18 years (KIDS5 and KIDS17), a

\(^{17}\)Exclusions include: ethnicities other than black or white; households with female heads (as no information on husbands is available); women who are retired, disabled, students, prisoners or employed in agriculture (or whose husbands are employed in agriculture); women residing outside of the North American continent; women older than 64; and women with missing or unreliable data (such as experience greater than age).

\(^{18}\)Equivalently, among those in the labor force, 5.9% are classified as UN.
dummy variable for black women (BLACK) and age (AGE). Prior work experience could affect both labor force decisions and job opportunities. The actual number of years worked since the age of 18 (EXP) is used to capture this effect. Regional effects are captured by city size and area of residence. The dummy variable SMSA represents residency in a SMSA, and the three dummy variables REGNC, REGS and REGW represent residency in North Central, Southern and Western areas of the U.S. continent, respectively. In order to capture income effects on a woman's labor force and employment decisions, we use her nonlabor income (WNLINC) and her husband's labor and nonlabor incomes (HLINC and HNLINC). The potential health effect on labor force and employment statuses is controlled for by using a dummy variable indicating physical condition limiting some types of work (WPHLIM). Finally, we include the local unemployment rate (UNEMPR) in order to capture differing demand conditions across areas.

4. RESULTS

Table 2 reports maximum likelihood estimates of the generalized censored probit log-likelihood function specified in equation (9). For the most part, the direction of variable impacts conforms to our prior expectations of their effect on LF, in column 2, and EMP in column 3. Individuals with higher educational levels (relative to the excluded less than high school degree group) are significantly more likely to be in the LF, with college graduates significantly more likely to be EMP. Women with more experience are significantly more likely, and older women significantly less likely to be both in the LF and EMP. This may imply a moderating impact of AGE on EXP relative to both LF and EMP outcomes. The existence of children in the household is associated with lower probabilities of both LF entry and EMP outcome, with the impact far
more pronounced in both significance and magnitude for households with children younger than 6. Black women are more likely to be in the LF, but less likely to be EMP, implying a higher unemployment rate relative to white women which is often observed in economy-wide data.

Viewing income effects on women’s labor force and employment decisions, our results show that higher labor income from the husband is associated with lower LF participation with an insignificant on EMP while nonlabor income has a significant impact only by reducing the EMP likelihood as HNLINC rises. Regional effects are generally insignificant determinants of either LF or EMP, with the exceptions being that women living in a SMSA or in an area with a higher local unemployment rate are less likely to be in the LF. Our results also estimate that the correlation between the LF and EMP process is significant, with a point estimate of .661.

The final two columns in Table 2 represent estimates of $P_1$, the conditional probability that reported UN status corresponds to true UN status, and $P_2$, the conditional probability that an OLF women is misclassified as UN.\footnote{Equation (6) defines $P_1$ and $P_2$ in greater detail. In the estimation of equation (9), both $P_1$ and $P_2$ are parameterized as cumulative normal density functions of all of the independent variables in the model.} Our results indicate that the only significant determinants of $P_1$ are the woman’s age, her husband’s non-labor income and the indicator for living in an SMSA, each of which is associated with a lower conditional probability that the observed and true unemployed statuses coincide. With respect to $P_2$, women who are older or have young children in the household, women whose husbands have greater labor income, and women from areas with higher local unemployment rates or from the south or west have significantly reduced likelihoods of having characteristics comparable to an OLF individual but being misclassified as being unemployed. In contrast, black women and those with greater labor market experience have a
significantly larger $P_2$ probability.

In sum, our generalized censored probit results in Table 2 allow us to determine not only a covariate’s impact on labor force participation decisions and employment outcomes but also its effect on the likelihood that an individual with characteristics comparable to OLF or UN individuals is misclassified as UN or OLF. For example, women with 1 or more child under 6 years old in the household are less likely to be in labor force, less likely to be employed, and, as their status is often reported as “housewife,” less likely to be misclassified as UN when they are truly OLF.\(^\text{20}\) Alternatively, women with greater actual labor market experience are more likely to be both in the labor force and employed, and are more likely to be misclassified as UN when, in fact, they are truly OLF. This latter impact may be due to a desire to maintain unemployment insurance eligibility by reporting search activity when, in reality, the status is observationally indistinguishable from OLF. Finally, black women are more likely to be in the labor force and less likely to be employed, with a higher likelihood that their OLF status is misclassified as UN. The initial impacts on LF and EMP imply a higher unemployment rate for black women (relative to white females), while the latter effect indicates that reported unemployment rate for black females may be too high due to misclassification of OLF as UN.

For inferences from our generalized censored probit models to provide reliable estimates of the LF, EMP, $P_1$ and $P_2$ processes, the underlying model must be correctly specified. The appendix develops both Hausman (HT) and Hausman score (HST) tests of the null hypothesis that our empirical specification of equation (9) is satisfactory. Results of these tests reported in Table 2 demonstrates that neither test rejects the null. We thus conclude that our representation

\(^{20}\)A comparable example is older women, who may have never entered the labor force or who may have retired.
of the generalized censored probit model is appropriate.

A primary objective for developing the generalized censored probit likelihood function in equation (9) was that it nests both the censored probit model used when UN and OLF are considered distinct states (specified in equation 4) as well as the Poirier probit specification used when UN and OLF are indistinguishable (given in equation 5). Our generalized censored probit function (9) thus permits us to determine if the censored probit model is appropriate, which occurs when $P_1 = 1 - P_2 = 1$; if the Poirier probit model is supported, which implies that $P_1 = P_2$; or if neither is confirmed due to the failure to consider possible ambiguity of UN and OLF classifications, which would arise if $P_1 > 0$ and/or $P_2 < 1$ (but are unequal to one another). Table 3 contains likelihood ratio, Wald and LM tests of these restrictions based on our estimated generalized censored probit model. Based on each of our three tests, in all cases our model rejects the restrictions implied by the censored probit model as well as those implied by the Poirier probit model.

We thus conclude that the Poirier probit specification, which treats UN and OLF statuses as indistinguishable, is not an adequate representation of the labor market environment represented by our data. Indeed, correct inferences may be drawn only when EMP, UN and OLF are each treated as distinct labor market states. However, we find that the censored probit specification of these three states is insufficiently general to acceptably capture the classification ambiguities inherent in our (and all similar) data sets. By constraining reported UN and OLF statuses to be true indications of a woman’s labor force situation, the censored probit specification ignores the very real likelihood that women with characteristics indistinguishable
from OLF (UN) individuals are misclassified as UN (OLF). 21

Having shown that appropriate modeling of labor force statuses requires consideration of distinct EMP, UN and OLF states and that classification ambiguities are likely to be present, it is important to determine the degree to which the estimated misclassification of UN (OLF) women as OLF (UN) results in over or under estimates of unemployment rates. As discussed above, if the sole classification ambiguity arises due to misclassified UN women \( (P_1 < 1) \), estimates of the unemployment rate would be overstated. Conversely, if the sole classification ambiguity arises among OLF women \( (P_2 > 0) \), estimated unemployment rates would be too low. Finally, if both classification ambiguities are present, estimates of the unemployment rate could be either too high or too low depending on the relative degree of misclassification.

Predicted probabilities generated from our generalized censored probit estimates are presented in Table 4. Panel 4a contains conditional probability estimates along with standard errors and 95% confidence intervals. We estimate that \( P_1 \), the probability that a woman with attributes consistent with true UN status is correctly reported as UN, equals 47%, with confidence bounds of 23 to 71%. The comparable estimate of \( P_2 \), the likelihood that a woman with OLF characteristics is misclassified as UN, equals approximately 12%, with 95% confidence bounds of 5 to 20%. Thus our estimates imply classification ambiguities for both groups, as \( P_1 \) is

21 For completeness, we report maximum likelihood estimates of the censored and Poirier probit models in Appendix Table 1. For the most part, the inferences that may be drawn from these results are comparable to those arising from the generalized censored probit model and will not be discussed here. Note that the Poirier probit model may not identify LF and EMP equations. We have ascribed the estimates to be LF or EMP due to their similarity to the generalized censored probit estimates. Also note that the estimates of \( \rho \) in Appendix Table 1 differ in sign and significance from that in Table 2. We believe this difference may be due to model misspecification in the censored or Poirier models relative to the generalized censored probit specification.
It is also possible to compute the conditional probabilities that an individual with characteristics consistent with true UN status is reported as UN or OLF. Panel 4a finds these estimates to be 49% and 22% respectively, and also provides confidence bounds for these estimates.

The impact of these estimated classification ambiguities on projected unconditional probabilities of EMP, UN and OLF is presented in Panel b of Table 4. As our generalized censored probit model did not consider potential misclassification of EMP, the sample and estimated probability of EMP both equal 69.5%. While the sample proportion of UN equals 4.4%, our model estimates that, after adjusting for potential classification ambiguities, the actual unemployment rate is 7.6% (with 95% confidence bounds of 4.5 to 10.7%). Thus the failure to control for misclassification of UN and OLF women in net results in an underestimate of the proportion who are UN of nearly 73% of the sample proportion of UN. This underestimate of UN is, by definition, offset by an overestimate of the probability of OLF. In contrast to the sample proportion of 26.2%, our estimate of this likelihood is 22.9% (with confidence bounds from 19.6 to 26.2%). Our result demonstrate that failure to adjust estimates of UN and OLF for potential misclassification of women’s statuses may lead to incorrect inferences as to the degree of UN (OLF) in the labor market.

5. CONCLUSION

This paper has developed a generalized censored probit likelihood function that nests both the Poirier probit and censored probit as special cases. This likelihood function allows us to test the appropriateness of the representation of the labor market as two distinct states—employed or not employed, implying that the Poirier probit specification is appropriate—or three distinct

\[ P_3 \text{ significantly less than one while } P_2 \text{ significantly exceeds zero.}^{22} \]

\[ \text{It is also possible to compute the conditional probabilities that an individual with characteristics consistent with true UN status is reported as UN or OLF. Panel 4a finds these estimates to be 49% and 22% respectively, and also provides confidence bounds for these estimates.} \]
states—EMP, UN or OLF, represented using the censored probit specification. In addition, our
generalized censored probit model permits parameterization and estimation of the degree of
empirical ambiguity between individuals reported as UN or OLF relative to individuals with
characteristics distinguishing them as truly UN or OLF.

Our empirical results demonstrate that the labor force statuses are best represented with
three distinct categories. However, the censored probit specification of this process is not
adequate as it fails to consider possible sample classification ambiguities. The generalized
censored probit estimates show that the impact of most covariates are consistent with our
expectations. Further, the model specification utilized satisfies both the Hausman and Hausman
Score tests as an appropriate formulation of the model. Estimates of UN and OLF probabilities
based on our model show that failure to incorporate classification ambiguities results in UN rates
that are understated and OLF rates that are overstated.

Our generalized censored probit model provides a powerful new tool with which to
determine the number of independent states that underlie an economic process and the degree of
classification ambiguity present in sample data. When either issue is of interest, or when more
accurate measures of event likelihoods in the presence of possible misclassifications is desired,
estimation of our generalized censored probit model is appropriate.
Appendix: Specification Tests

The reliability of statistical inferences based on the generalized censored probit model (9) is subject to whether the model is correctly specified. In this appendix, we develop some specification tests for the model. The statistics we derive are straightforward extensions of Newey (1987) and Peters and Smith (1991).

For notational convenience, we use \( \lambda_0 = (\theta_0', \lambda_0') \) to denote the true value of the parameter vector \( \lambda \) for the generalized censored probit model. In addition, we use subscripts "p" and "g" to refer to the Poirier and generalized censored probit models, respectively. Thus \( \hat{\theta}_p \) and \( \hat{\theta}_g = (\hat{\theta}_g', \hat{\gamma}_g')' \) indicate the maximum-likelihood estimators of \( \theta \) and \( \lambda \) for the Poirier and generalized censored probit models, respectively, while \( s_p(\theta) = \partial l_p(\theta)/\partial \theta \) and \( s_g(\lambda) = \partial l_g(\lambda)/\partial \lambda \) denote score vectors.\(^a\) We further define the Hessian matrices for the models by \( H_p(\theta) = \partial s_p(\theta)/\partial \theta' \) and \( H_g(\lambda) = \partial s_g(\lambda)/\partial \lambda' \). If we then let \( J_p(\theta) = [-H_p(\theta)]^{-1} \) and \( J_g(\lambda) = [-H_g(\lambda)]^{-1} \) the variance-covariance matrices \( V(\hat{\theta}_p) \) and \( V(\hat{\lambda}_g) \), can be consistently estimated by \( J_p(\hat{\theta}_p) \) and \( J_g(\hat{\lambda}_g) \), respectively. Finally, letting \( M = (I_q, 0_{q,r}) \) where \( q \) and \( r \) are the number of parameters in \( \theta \) and \( \gamma \), respectively, \( V(\hat{\theta}_g) = MJ_g(\hat{\lambda}_g)M' \).

The foundation of our specification test is the fact that \( \hat{\theta}_p \) is a consistent estimator of \( \theta_0 \) if the generalized censored probit model (9) is correctly specified. Thus, under the null hypothesis \( (H_g^g) \) that the general model is correctly specified, the difference between \( \hat{\theta}_p \) and \( \hat{\theta}_g \) should be small.\(^b\) Based upon this observation, we can construct a Hausman (1978) test statistic:

\(^a\)Score vectors for individual i are denoted \( S_p(\theta) \) and \( S_g(\lambda) \).

\(^b\)As mentioned earlier, which parts of \( \hat{\theta}_p = (\hat{\beta}_{f,p}', \hat{\beta}_{p,emp,p}', \hat{\rho}_p') \) should be treated as the estimates of \( \beta_{lf} \) and \( \beta_{emp} \) cannot be determined in the Poirier model. However, this is not a serious problem in our specification tests. Comparing \( \hat{\theta}_p \) and \( \hat{\theta}_g \), we can choose the part of \( \hat{\theta}_p \) close to \( \hat{\beta}_{f,g} \) (\( \hat{\beta}_{emp,g} \)) as the Poirier estimate of \( \beta_{lf} \) (\( \beta_{emp} \)).
\[ HT_g = (\hat{\theta}_p - \hat{\theta}_g)'[V(\hat{\theta}_p - \hat{\theta}_g)]^{-1}(\hat{\theta}_p - \hat{\theta}_g), \]  

(A1)

which, under \(H_0\), is asymptotically \(\chi^2\)-distributed with \(q\) degrees of freedom (\(q\) equals the number of parameters in \(\theta\)).

In practice, the variance-covariance matrix \(V(\hat{\theta}_p - \hat{\theta}_g)\) must be estimated. Following Hausman (1978), it can be shown that \(V(\hat{\theta}_p - \hat{\theta}_g) = V(\hat{\theta}_p) - V(\hat{\theta}_g)\). Thus, \(V(\hat{\theta}_p - \hat{\theta}_g)\) can be easily estimated by the difference between \(J_p(\hat{\theta}_p)\) and \(MJ_g(\hat{\lambda}_g)M'\). Unfortunately, this estimate is not necessarily positive definite, and the Hausman statistic computed with this estimate could be negative. In order to avoid this problem, we estimate \(V(\hat{\theta}_p - \hat{\theta}_g)\) following Newey (1987, p. 130). Defining \(B_{g, p}(\hat{\theta}_p, \hat{\lambda}_g) = [J_p(\hat{\theta}_p), -MJ_g(\hat{\lambda}_g)]\) and \(D_{g, p}(\hat{\theta}_p, \hat{\lambda}_g) = \sum d_{g, i}(\hat{\theta}_p, \hat{\lambda}_g)'d_{g, i}(\hat{\theta}_p, \hat{\lambda}_g)\), where \(d_{g, i}(\hat{\theta}_p, \hat{\lambda}_g) = [s_{p, i}(\hat{\theta}_p), s_{g, i}(\hat{\lambda}_g)]\), it can be shown that:

\[ \hat{V}(\hat{\theta}_p - \hat{\theta}_g) = B_{g, p}(\hat{\theta}_p, \hat{\lambda}_g)'D_{g, p}(\hat{\theta}_p, \hat{\lambda}_g)B_{g, p}(\hat{\theta}_p, \hat{\lambda}_g) \]

is a consistent estimator of \(V(\hat{\theta}_p - \hat{\theta}_g)\).

An alternate specification test may be developed based on a Hausman score test (Peters and Smith (1991)). It can be shown that under \(H_0^g\), \(E[s_p(\hat{\theta}_o)] = 0\). Thus if \(H_0^g\) is correct, \(N^{-1}s_p(\hat{\theta}_g)\) should be close to zero, since \(\hat{\theta}_g\) is a consistent estimator of \(\theta_o\). Accordingly, any significant deviation of \(N^{-1}s_p(\hat{\theta}_g)\) from zero can be regarded as a sign of misspecification. Under \(H_0^g\), the Hausman score test statistic:

\[ HST_g = s_p(\hat{\theta}_g)'[V(s_p(\hat{\theta}_g))]^{-1}s_p(\hat{\theta}_g). \]

(A3)

is asymptotically \(\chi^2\)-distributed with degrees of freedom equal to \(q\). Following Peters and Smith (1991, pp. 181-182), the variance-covariance matrix \(V[s_p(\hat{\theta}_g)]\) can be consistently estimated by:

\[ \hat{V}[s_p(\hat{\theta}_g)] = [J_q, H_p(\hat{\theta}_g)MJ_g(\hat{\lambda}_g)D_g(\hat{\theta}_g, \hat{\lambda}_g)]\left[I_q, H_p(\hat{\theta}_g)MJ_g(\hat{\lambda}_g)D_g(\hat{\theta}_g, \hat{\lambda}_g)'\right]. \]

(A4)

Note that \(HST_g\) is computed by using \(\hat{\lambda}_g\) only. In contrast to \(HT_g\), it does not require
computation of $\hat{\theta}_p$. Nonetheless, following Peters and Smith, it can be shown that the two
statistics are asymptotically identical under $H_0^\beta$. 
## Appendix Table 1

Censored and Poirier Probit Estimates

<table>
<thead>
<tr>
<th>Regressors</th>
<th>Labor Force</th>
<th>Employment</th>
<th>Labor Force (??) (^a)</th>
<th>Employment (??) (^b)</th>
<th>Prob. of UN Given not EMP with restriction (P_1=P_2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Censored Probit Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.747(^*)</td>
<td>0.541 ((1.264))</td>
<td>1.476(^*)</td>
<td>3.219(^*)</td>
<td>2.084(^*)</td>
</tr>
<tr>
<td>HSGRAD</td>
<td>0.172(^*)</td>
<td>0.357(^*)</td>
<td>0.303(^*)</td>
<td>0.045</td>
<td>-0.092</td>
</tr>
<tr>
<td>COGRAD</td>
<td>0.622(^*)</td>
<td>0.404(^*)</td>
<td>0.399(^*)</td>
<td>0.547(^*)</td>
<td>0.345</td>
</tr>
<tr>
<td>KIDS5</td>
<td>-0.512(^*)</td>
<td>-0.034 ((0.205))</td>
<td>-0.424(^*)</td>
<td>-0.346(^*)</td>
<td>-0.445(^*)</td>
</tr>
<tr>
<td>KIDS17</td>
<td>-0.053(^*)</td>
<td>-0.005 ((0.115))</td>
<td>-0.061</td>
<td>-0.079</td>
<td>-0.004</td>
</tr>
<tr>
<td>BLACK</td>
<td>0.081 ((1.060))</td>
<td>-0.438(^*) ((3.759))</td>
<td>0.426(^*)</td>
<td>-0.474(^*)</td>
<td>0.627(^*)</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.059(^*)</td>
<td>0.016 ((0.781))</td>
<td>-0.033(^*)</td>
<td>-0.053(^*)</td>
<td>-0.071(^*)</td>
</tr>
<tr>
<td>EXP</td>
<td>0.081(^*)</td>
<td>0.010 ((0.364))</td>
<td>0.157</td>
<td>0.030(^*)</td>
<td>0.062(^*)</td>
</tr>
<tr>
<td>SMSA</td>
<td>-0.118(^*)</td>
<td>0.204(^*) ((1.921))</td>
<td>-0.209(^*) ((1.854))</td>
<td>0.123</td>
<td>-0.358(^*)</td>
</tr>
<tr>
<td>REGNC</td>
<td>0.041 ((0.441))</td>
<td>0.185 ((1.262))</td>
<td>0.061 ((0.386))</td>
<td>0.097 ((0.505))</td>
<td>-0.239</td>
</tr>
<tr>
<td>REGS</td>
<td>-0.002 ((0.028))</td>
<td>0.378(^*) ((2.741))</td>
<td>0.183 ((1.201))</td>
<td>0.046 ((0.271))</td>
<td>-0.502(^*)</td>
</tr>
<tr>
<td>REGW</td>
<td>-0.106 ((1.098))</td>
<td>0.466(^*) ((2.578))</td>
<td>0.314 ((1.563))</td>
<td>-0.283 ((1.531))</td>
<td>-0.767(^*) ((3.328))</td>
</tr>
<tr>
<td>WNLINC</td>
<td>-0.011 ((0.108))</td>
<td>0.021 ((0.084))</td>
<td>0.405 ((0.922))</td>
<td>-0.070 ((0.670))</td>
<td>-0.199 ((0.666))</td>
</tr>
<tr>
<td>HLINC</td>
<td>-0.057(^*) ((4.690))</td>
<td>0.028 ((0.820))</td>
<td>-0.107 ((4.845))</td>
<td>0.005 ((0.156))</td>
<td>-0.092(^*) ((2.391))</td>
</tr>
<tr>
<td>HNLINC</td>
<td>-0.017 ((0.426))</td>
<td>0.297(^*) ((2.032))</td>
<td>0.231 ((1.486))</td>
<td>-0.143 ((2.186))</td>
<td>-0.435(^*) ((1.824))</td>
</tr>
<tr>
<td>WPHLIM</td>
<td>-0.381(^*) ((4.104))</td>
<td>-0.537(^*) ((2.632))</td>
<td>-0.081 ((0.252))</td>
<td>-0.649(^*) ((4.276))</td>
<td>0.155 ((0.895))</td>
</tr>
<tr>
<td>UNEMPR</td>
<td>-5.940(^*) ((4.480))</td>
<td>-2.065 ((0.718))</td>
<td>-6.924(^*) ((2.701))</td>
<td>-2.632 ((1.047))</td>
<td>-3.649 ((1.350))</td>
</tr>
</tbody>
</table>

| **Poirier Probit Model** | | | | | |
| \(p\)     | -0.133 \((0.176)\) | -0.047 \((0.053)\) | | | |
| Log-likelihood | -1650.1 | -1336.2 | -268.7 | | |
| # of observation | 2,706 | 2,706 | 826 | | |

\(^a\) Chosen compared with the generalized probit results.
\(^b\) Absolute value of t-statistic in parentheses.

\*Significant at \(\alpha = .01\) (two tail test).

\**Significant at \(\alpha = .10\) (two tail test).
### Table 1
Variable Definition and Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LF</td>
<td>= 1 if in LF (EMP or UN); = 0 otherwise (OLF)</td>
<td>.738</td>
<td>.440</td>
</tr>
<tr>
<td>EMP</td>
<td>= 1 if employed; = 0 otherwise</td>
<td>.695</td>
<td>.461</td>
</tr>
<tr>
<td>HSGRAD</td>
<td>= 1 if high school (not college) graduate; = 0 otherwise</td>
<td>.588</td>
<td>.492</td>
</tr>
<tr>
<td>COGRAD</td>
<td>= 1 if college graduate; = 0 otherwise</td>
<td>.220</td>
<td>.414</td>
</tr>
<tr>
<td>AGE</td>
<td>years of age</td>
<td>36.63</td>
<td>10.81</td>
</tr>
<tr>
<td>EXP</td>
<td>years of actual work experience</td>
<td>10.191</td>
<td>7.709</td>
</tr>
<tr>
<td>HLINC</td>
<td>husband’s labor income (in $10,000s)</td>
<td>2.646</td>
<td>2.558</td>
</tr>
<tr>
<td>HNLINC</td>
<td>husband’s nonlabor income (in $10,000s)</td>
<td>.216</td>
<td>.723</td>
</tr>
<tr>
<td>WNLINC</td>
<td>wife’s nonlabor income (in $10,000s)</td>
<td>.036</td>
<td>.285</td>
</tr>
<tr>
<td>WPHLIM</td>
<td>= 1 if physical handicap limits some types of job; = 0 otherwise</td>
<td>.101</td>
<td>.302</td>
</tr>
<tr>
<td>BLACK</td>
<td>= 1 if black; = 0 if white</td>
<td>.237</td>
<td>.425</td>
</tr>
<tr>
<td>KIDS5</td>
<td>number of children of age ≤ 5 in household</td>
<td>.508</td>
<td>.774</td>
</tr>
<tr>
<td>KIDS17</td>
<td>number of children of age 6-17 in household</td>
<td>.799</td>
<td>1.029</td>
</tr>
<tr>
<td>SMSA</td>
<td>= 1 if living in SMSA; = 0 otherwise</td>
<td>.565</td>
<td>.496</td>
</tr>
<tr>
<td>REGNC</td>
<td>= 1 if living in North Central region; = 0 otherwise</td>
<td>.213</td>
<td>.409</td>
</tr>
<tr>
<td>REGS</td>
<td>= 1 if living in Southern region; = 0 otherwise</td>
<td>.412</td>
<td>.492</td>
</tr>
<tr>
<td>REGW</td>
<td>= 1 if living in Western region; = 0 otherwise</td>
<td>.170</td>
<td>.376</td>
</tr>
<tr>
<td>UNEMPR</td>
<td>unemployment rate in county of residence</td>
<td>.055</td>
<td>.025</td>
</tr>
</tbody>
</table>
## Table 2
Generalized Censored Probit Estimates

<table>
<thead>
<tr>
<th>Regressors</th>
<th>Labor Force</th>
<th>Employment</th>
<th>Prob. classified as UN given UN attributes ($P_1$)</th>
<th>Prob. classified as UN given OLF attributes ($P_2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.543* (5.614)*</td>
<td>3.305* (7.727)</td>
<td>6.727** (2.338)</td>
<td>2.411* (3.669)</td>
</tr>
<tr>
<td>HSGRAD</td>
<td>0.368* (3.606)</td>
<td>-0.015 (0.113)</td>
<td>-0.393 (0.643)</td>
<td>-0.318 (1.300)</td>
</tr>
<tr>
<td>COGRAD</td>
<td>0.465* (3.686)</td>
<td>0.696* (3.465)</td>
<td>0.981 (1.154)</td>
<td>0.301 (0.872)</td>
</tr>
<tr>
<td>KIDS5</td>
<td>-0.417* (7.803)</td>
<td>-0.464* (4.384)</td>
<td>-0.687 (1.620)</td>
<td>-0.765* (4.599)</td>
</tr>
<tr>
<td>KIDS17</td>
<td>-0.089** (1.982)</td>
<td>-0.040 (0.670)</td>
<td>-0.422 (1.514)</td>
<td>0.004 (0.043)</td>
</tr>
<tr>
<td>BLACK</td>
<td>0.283** (1.771)</td>
<td>-0.469* (3.103)</td>
<td>0.365 (0.627)</td>
<td>0.709** (2.290)</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.042* (5.503)</td>
<td>-0.055* (6.621)</td>
<td>-0.160* (2.841)</td>
<td>-0.069* (4.303)</td>
</tr>
<tr>
<td>EXP</td>
<td>0.151* (11.08)</td>
<td>0.034* (2.800)</td>
<td>0.016 (0.326)</td>
<td>0.088** (2.122)</td>
</tr>
<tr>
<td>SMSA</td>
<td>-0.174** (1.909)</td>
<td>0.144 (1.188)</td>
<td>-1.707** (2.560)</td>
<td>0.253 (0.949)</td>
</tr>
<tr>
<td>REGNC</td>
<td>0.135 (1.018)</td>
<td>-0.013 (0.071)</td>
<td>0.241 (0.326)</td>
<td>-0.275 (0.912)</td>
</tr>
<tr>
<td>REGS</td>
<td>0.183 (1.590)</td>
<td>0.045 (0.292)</td>
<td>0.205 (0.314)</td>
<td>-0.865* (2.804)</td>
</tr>
<tr>
<td>REGW</td>
<td>0.198 (1.291)</td>
<td>-0.268 (1.541)</td>
<td>-0.522 (0.719)</td>
<td>-1.034** (2.460)</td>
</tr>
<tr>
<td>WNLINC</td>
<td>0.512 (1.637)</td>
<td>-0.090 (0.873)</td>
<td>-0.883 (0.560)</td>
<td>-2.295 (0.512)</td>
</tr>
<tr>
<td>HLINC</td>
<td>-0.101* (5.294)</td>
<td>0.010 (0.329)</td>
<td>0.126 (0.706)</td>
<td>-0.202** (2.537)</td>
</tr>
<tr>
<td>HNLINC</td>
<td>0.194 (1.517)</td>
<td>-0.153* (2.579)</td>
<td>-0.850** (1.909)</td>
<td>-0.741 (1.253)</td>
</tr>
<tr>
<td>WPHLIM</td>
<td>-0.272 (0.911)</td>
<td>-0.689* (4.460)</td>
<td>-0.172 (0.246)</td>
<td>0.014 (0.041)</td>
</tr>
<tr>
<td>UNEMPR</td>
<td>-6.299** (3.610)</td>
<td>-3.709 (1.633)</td>
<td>7.227 (0.827)</td>
<td>-10.68** (1.768)</td>
</tr>
</tbody>
</table>

\[ \rho \] 0.661* (2.745)

<table>
<thead>
<tr>
<th></th>
<th>Log of likelihood</th>
<th># of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1581.38</td>
<td>2,706</td>
</tr>
</tbody>
</table>

Specification Tests

<table>
<thead>
<tr>
<th></th>
<th>Hausman Test (HT, df = 35)</th>
<th>Hausman Score Test (HST, df = 35)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>18.7 (p = 0.99)*</td>
<td>27.4 (p = 0.82)*</td>
</tr>
</tbody>
</table>

*Absolute value of t-statistic in parentheses.

b p-values.

Significant at \( \alpha = .01 \) (two tail test).

Significant at \( \alpha = .10 \) (two tail test).
## Table 3

Tests for Restricted models

<table>
<thead>
<tr>
<th>Tests for restricted models</th>
<th>The Poirier model ((P_1 = P_2)) ((df = 17))</th>
<th>The Censored model ((P_1 = 1 &amp; P_2 = 0)) ((df = 34))</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>47.1 (p = 0.00)</td>
<td>137.3 (p = 0.00)</td>
</tr>
<tr>
<td>Wald</td>
<td>24.9 (p = 0.10)</td>
<td>738.3 (p = 0.00)</td>
</tr>
<tr>
<td>LM</td>
<td>68.2 (p = 0.00)</td>
<td>182.4 (p = 0.00)</td>
</tr>
</tbody>
</table>

\(^a\)P-values are in the parentheses ( ).

\(^b\)Tests for the restriction \(\gamma_1 = \gamma_2\).

\(^c\)The censored model is equivalent to the general model with two sets of restrictions on \(\gamma_1\) and \(\gamma_2\). The first set of restriction is that the constant term in \(\gamma_1\) is arbitrarily large while all other coefficients in \(\gamma_1\) equal zeros. Another set of restrictions is that the constant term in \(\gamma_2\) is a negative number whose absolute value is large while all other coefficients in \(\gamma_2\) equal zeros. We chose three for the constant term in \(\gamma_1\) and negative three for the constant term in \(\gamma_2\). The computed Wald and LM statistics are for testing these restrictions.
### Table 4
Probabilities Predicted Based on the Generalized Censored Probit Estimates

#### A. Conditional Probabilities

<table>
<thead>
<tr>
<th>Conditional Prob. of reported UN given UN attributes ((P_1))</th>
<th>From Generalized Censored Probit Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.470&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>[0.124]&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>{0.227, 0.713}&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Conditional Prob. of reported UN given OLF attributes ((P_2))</td>
<td>0.121&lt;sup&gt;d&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>[0.038]</td>
</tr>
<tr>
<td></td>
<td>{0.047, 0.195}</td>
</tr>
<tr>
<td>Conditional Prob. of UN attributes given reported UN</td>
<td>0.492&lt;sup&gt;e&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>[0.074]</td>
</tr>
<tr>
<td></td>
<td>{0.347, 0.637}</td>
</tr>
<tr>
<td>Conditional Prob. of UN attributes given reported OLF</td>
<td>0.224&lt;sup&gt;f&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>[0.083]</td>
</tr>
<tr>
<td></td>
<td>{0.061, 0.387}</td>
</tr>
</tbody>
</table>

#### B. Unconditional Probabilities

<table>
<thead>
<tr>
<th>Unconditional Prob. of Employment</th>
<th>From Sample</th>
<th>From Generalized Censored Probit Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.695</td>
<td>0.695&lt;sup&gt;g&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.008]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>{0.677, 0.711}</td>
</tr>
<tr>
<td>Unconditional Prob. of Unemployment</td>
<td>0.044</td>
<td>0.076&lt;sup&gt;h&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.016]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>{0.045, 0.107}</td>
</tr>
<tr>
<td>Unconditional Prob. of Out of labor force</td>
<td>0.262</td>
<td>0.229&lt;sup&gt;i&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.017]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>{0.196, 0.262}</td>
</tr>
</tbody>
</table>

<sup>a</sup>Computed by the sample mean of \(P_1\) for all nonworkers in the sample.

<sup>b</sup>Asymptotic standard errors are in the parentheses [ ].

<sup>c</sup>95% confidence intervals are in the parentheses { }.

<sup>d</sup>Computed by the sample mean of \(P_2\) for all nonworkers in the sample.

<sup>e</sup>Computed by the sample mean of \(P_1\) for all nonworkers in the sample.

<sup>f</sup>Computed by the sample mean of \((1-P_1)(\Phi(X\beta_{\text{M}}-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)))/(1-P_2)(\Phi(X\beta_{\text{M}}-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho))+(1-P_2)[1-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)])\)

for all nonworkers in the sample.

<sup>g</sup>Computed by the sample mean of \((1-P_1)(\Phi(X\beta_{\text{M}}-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)))/(1-P_2)(\Phi(X\beta_{\text{M}}-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho))+(1-P_2)[1-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)])\)

for all nonworkers in the sample.

<sup>h</sup>Computed by the sample mean of \(F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)\) for all sample observations.

<sup>i</sup>Computed by the sample mean of \([\Phi(X\beta_{\text{M}})-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)]\) for all sample observations.

<sup>j</sup>Computed by the sample mean of \([1-F(X\beta_{\text{M}},X\beta_{\text{emp}}\rho)]\) for all sample observations.
REFERENCES


Günül, F. (1992), "New Evidence on Whether Unemployment and Out of Labor Force Are


Sundt, L. (1991), " ".