METHODOLOGICAL ISSUES IN THE EVALUATION OF CETA PROGRAMS: ENDOGENOUS PARTICIPATION, COMPLETION, AND PROGRAM ASSIGNMENT

Lee A. Lillard, Subal Kumbhakar

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PREFACE

This Note examines selected methodological issues for the evaluation of training programs similar to that of the Comprehensive Employment and Training Act (CETA). It addresses two aspects of the training programs that are treated only casually in the literature. First, in addition to the worker's endogenous participation and program-completion decisions, the authors include the program sponsors' endogenous decisions concerning the type of training received by the trainee (i.e., assignment to a program type) and the placement of the trainee in a job at the end of the training period. Second, the authors also include in their analysis various components of earnings (in terms of wage rates, hours per week, and weeks worked), as well as individual differences in the long-run level and growth of these components, and transitory variations.

These models should be of interest to researchers involved in the evaluation of similar government-sponsored programs. This study was sponsored by the Employment and Training Administration, U.S. Department of Labor.

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SUMMARY

Government-sponsored training programs were initiated in 1962 with the passage of the Manpower Development Training Act (MDTA). Since that time, the government has continued to sponsor training on a large scale with the passage of the Comprehensive Employment and Training Act (CETA) in 1973 and the Job Partnership Training Act (JPTA) in 1982. Over the subsequent 35 years, studies concerned with the effects of these programs have increased steadily. Although numerous studies have been concerned with methodological issues, particularly self-selection into training, several methodological shortcomings remain. Those are the subject of this research.

Empirical studies frequently use detailed characteristics of training programs but without recognizing the econometric implications. However, those researchers who discuss econometric methods have ignored potentially important aspects of the training programs, and frequently the components of earnings. Each of these issues helps explain why estimates of training program effects may be unstable across studies that have used different time frames, different composition with respect to program content, and different specifications of the earning equation.

There are numerous training programs. Within CETA, for example, are classroom training, on-the-job training, public service employment, and miscellaneous other special programs. In addition, a participant may or may not complete a given training program. Some of those who complete the training program are placed on jobs; others are not. Further, some aspects of the training experience may be effective while others are not. Numerous studies have been concerned with the endogeneity of training participation, or perhaps its completion. However, each aspect of the training process should be considered as potentially endogenous, not just the participation decision.

Concentration on the broad concept of earnings masks the potentially rich information on the components of earnings and changes in earnings—that is, wage rates, weeks worked, and hours per week—
and permanent versus transitory components of change. Which component is associated with the widely cited low earnings prior to training, what are the sources of improved earnings after training, and how lasting are the improvements? These are more relevant questions.

Training decisions may depend on past earnings outcomes. For example, workers with low wage growth or abnormally low earnings in recent periods may be more likely to take training. Currently abnormal "transitorily" low wages reduce the opportunity cost or forgone earnings of training. Previous studies have demonstrated the presence of individual life cycle patterns (random level and growth components) and autoregression in earnings residuals (net of comprehensive sets of explanatory variables). Because of these factors, there will be correlations between training, and earnings and employment equations, both before and after training. The character of the training received by each worker is endogenous and must be modeled jointly with the evaluation of its effects.

An important feature of the models to be developed in the subsequent sections is that the return to training is determined by the character of the training received. An individual may be assigned by the local prime sponsor to different training programs. Government-sponsored training programs span a broad range of subprogram types (from classroom training, to training on the job, to public service employment).

The decision to complete training, once it has begun, depends on further information acquired during training. Training occurs over an extended period of time so that information and expectations may change. A good job offer may increase the opportunity cost and forgone earnings. The worker may revise expectations about training benefits as he proceeds through training. These factors will influence the decision to complete training once it has begun.

The standard empirical treatment of training effects is as an earnings shift. Earnings are increased by a constant amount following training. It is equally plausible that training would enhance wage or earnings growth as well and that the effects of training may attenuate over time. Training may enhance earnings other than through wages. It may enhance employability and thus reduce turnover and unemployment. In
some cases it actually provides direct job placement of the trainee. Earnings are increased through either increased weeks worked, reduced unemployment, or increased hours per week worked, full time instead of part time employment.

This Note develops an econometric methodology to deal with these aspects of training decisions and their consequences. The issues addressed include: (1) the various aspects of a CETA type of training program--training subprograms, completion of training, and job placement; (2) the effects of these different aspects of training; (3) the various components of earnings that may be affected by training including wages, weeks worked, and hours per week, in addition to the usual variance components; (4) potential erosion of the effects of training over time; and (5) the endogeneity of assignment to training subprograms, the completion of the program of training, and placement in a job upon completion, in addition to the participation decision.

First, these issues are treated for the case where training decisions are predetermined to show that several of the potential specification errors arise even in that special case. The remainder of the Note is concerned with estimation and identification of parameters in the case where training decisions are endogenous. Both full information maximum likelihood (FIML) and multistage instrumental variable estimation procedures are used to motivate the conceptual restrictions required for identification.
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I. INTRODUCTION

Government-sponsored training programs were initiated in 1962 with the passage of the Manpower Development Training Act (MDTA). Since that time the government has continued to sponsor training on a large scale with the passage of the Comprehensive Employment and Training Act (CETA) in 1973 and the Job Partnership Training Act (JPTA) in 1982. Over the subsequent 35 years, the number of studies concerned with the effects of these programs has increased steadily over time. However, the empirical results have been largely inconclusive and have varied widely in the form of the analysis and the magnitude of estimated effects of training on earnings. Although numerous studies have been concerned with methodological issues, particularly self-selection into training, several methodological shortcomings remain that may give rise to unstable estimates of training effects.

A review of previous studies reveals that empirical studies frequently use detailed characteristics of training programs but without recognizing the econometric implications. However, researchers who discuss econometric methods have ignored potentially important aspects of the training programs and frequently the components of earnings. Each of these issues is related to explaining why estimates of training program effects may be unstable across studies that have used different time frames, different composition with respect to program content, and different specifications of the earning equation. This Note explores these aspects of training and its effects. The issues we address include: (1) the various aspects of a CETA type of training program--training subprograms, completion of training, and job placement; (2) the effects of these different aspects of training; (3) the various components of earnings that may be affected by training including wages, weeks worked, and hours per week, in addition to the usual variance components; (4) potential erosion of the effects of training over time; and (5) the endogeneity of assignment to training subprograms, the completion of the program of training, and placement in a job upon completion, in addition to the participation decision. Although past
studies have addressed many of these issues, they have been treated separately or incompletely. We explore these issues in a unified way and suggest approaches to estimation. To avoid clouding the issues that we want to stress, we make some admittedly unrealistic assumptions in other dimensions such as the availability of panel data both before and after training.

PREVIOUS STUDIES

Past studies have been either too simplistic in their concern with earnings and participation or too naive in their econometric implementation. Recent methodological developments have concentrated on estimating the earnings effects of participation. Heckman and Robb (1985) present an extensive discussion of "methods of estimating the impact of training on earnings when non-random selection characterizes the enrollment of persons into training." Although they have considered numerous issues related to this simple model, including the use of pre-training and post-training earnings and nonparticipants, and nonrandom selection, the appropriateness of the simple earnings-participation specification to CETA-like programs is questionable.

Ashenfelter and Card (1985) use longitudinal earnings of participants as well as controls to study the role of permanent and transitory earnings components in nonrandom selection into training. Following the earlier work of Ashenfelter (1978), they suggest that participation depends in particular on earnings just before entry into training. Their model is implemented with data from the CETA program. Bassi (1984) similarly was concerned with a subset of these issues and reports estimates of random and fixed effect models of CETA participation effects on earnings.

Although these studies\(^1\) are concerned with the use of longitudinal data and with the endogeneity of training, they ignore some important features of training programs and they do not consider the employment aspects of earnings. Many recent studies commissioned to evaluate the CETA program have considered these neglected issues, but usually

\(^1\)Another study in this basic category is by Cooley, McGuire, and Prescott (1979), although the authors do consider some employment effects as well.
separately. These include Bassi et al. (1983); Dickinson, Johnson, and West (1984); King and Geraci (1983). It is evident from these three studies that there is a substantial role played by the additional issues of wages versus employment and by the character of the training program experienced by the worker. However, these studies do not adequately deal with either the endogeneity of training or the permanent versus transitory nature of wages and employment.

Both Bassi et al. (1983) and Dickinson, Johnson, and West (1984) consider a decomposition of the effects of training on annual earnings into its effects on weeks worked, on average hours worked per week, and on the average wage rate. These studies show that the effect of training on earnings is primarily employment-related, by far the largest effect being for weeks worked, followed by hours per week, and then the wage rate. Bassi et al. (1983) show that these results differ somewhat by type of training received, but that the relative effects are stable. Levy (1982) suggests that these training programs may serve more of a role as an employment service than actually training less-skilled workers. Dickinson, Johnson, and West (1984) show that the magnitudes of the components differ between subgroups based on youth versus adults and men versus women.

The evaluation studies by Bassi et al. (1983) and Dickinson, Johnson, and West (1984) consider issues related to the character of the training program. There are basically three program types offered by CETA: Classroom training, on-the-job training, and public service employment. Although these studies do not agree on the magnitudes of the effects of the different programs, they do agree that the effects are different from one another. Dickinson, Johnson, and West (1984),

---

2In addition, Bassi et al. (1983) include weeks available for employment (in the labor force, especially for youth) and Dickinson, Johnson, and West (1984) include whether the longest job was in the public sector. King and Geraci (1983) consider several other short-term indicators of program success. Additional items include welfare status, welfare intensity, and placement job retention. Surprisingly, few studies have considered subsequent unemployment probabilities directly.

3Other program types include the private sector initiative program, direct referral, and for youth, the youth work experience program and summer work experience program.
considering adult as well as youth groups, find that classroom training typically has the largest positive effect, followed by roughly equal effects of on-the-job training and public service employment. For young men, on-the-job training is the most important source and for adult men all program effects are negative. Bassi et al. (1983) find that the only consistently positive effect for youths is public service employment.

The results of the evaluation studies seem to be fairly sensitive to the time period considered and to the length of time after the training that the effects are evaluated. Most of the studies are based on earnings one or two years after the training.

In a study of various sources and types of training undertaken in the private sector, Lillard and Tan (1986) found that the effects of training are greatest on earnings just after the training but that they deteriorate thereafter. With respect to who gets training, they find that the probability of taking various sources and types of training are differentially affected by labor market conditions and by the rate of technical change in the worker's industry. Westat (1982) suggests that for CETA programs the local primary sponsors (who actually run the training programs locally) base their decisions concerning the choice of program on the particular local labor market situation and on the potential employability of the individual worker.

While these studies as a group consider the relevant issues--endogeneity of training, the use of panel data, dimensions of training, and wage and employment components of earnings--each considers only a subset of the various issues.

SUMMARY OF ISSUES TO BE ADDRESSED

It is fairly uninformative to know only that a person has participated in a government-sponsored training program, or even that he completed one. There are numerous training programs. CETA, for example, has classroom training, on-the-job training, public service employment, and miscellaneous other programs. A participant may or may not complete a given training program. Some of those who complete the training program are placed on jobs; others are not. Therefore, participation may represent vastly different experiences. Further, some
aspects of the training experience may be effective while others are not. Numerous studies have been concerned with the endogeneity of training participation, or perhaps its completion. However, each stage of the training process should be considered as potentially endogenous, not just the participation decision.

Concentration on the broad concept of earnings masks the potentially rich information on the components of earnings and changes in earnings—that is, wage rates, weeks worked, and hours per week—and permanent versus transitory components of change. Which component is associated with the widely cited low earnings before training, what are the sources of improved earnings after training, and how lasting are the improvements? These are more relevant questions.

Training decisions may depend on past earnings outcomes. For example, workers with low wage growth or abnormally low earnings in recent periods may be more likely to take training. Currently abnormal "transitorily" low wages reduce the opportunity cost or forgone earnings of training. Previous studies have demonstrated the presence of individual life cycle patterns (random level and growth components) and autoregression in earnings residuals (net of comprehensive sets of explanatory variables). Because of these factors, there will be correlations between training and earnings and employment equations both before and after training. The character of the training each worker receives is endogenous and must be modeled jointly with the evaluation of its effects.

Another important feature of the models to be developed in the subsequent sections is that the actual return to training will be partially determined by the character of the training the worker receives. The local prime sponsor may assign an individual to different training programs. Government-sponsored training programs span a broad range of subprogram types (from classroom training to on-the-job training to public service employment). In manpower training programs, according to Westat (1982), assignment to a particular program depends on the "employability" of the worker, with the more "employable" assigned to public service employment.
The decision to complete training once it has begun, will depend on further information acquired during training. Training occurs over an extended period of time so that information and expectations may change. A good job offer may increase the opportunity cost and forgone earnings. The worker may revise expectations about training benefits as he proceeds through training. These factors will influence the decision to complete training once it has begun.

What are the effects of training? The standard empirical treatment of training effects is as an earnings shift. Earnings are increased by a constant amount following training. It is equally plausible that training would enhance wage or earnings growth as well and that the effects of training may attenuate over time. In this regard it is especially important to control for previous wage patterns. If workers with low wage growth enter training, then trained workers may have below-average wage growth, even though training had a positive effect.

Training may enhance earnings other than through wages. It may enhance employability and thus reduce turnover and unemployment. In some cases it actually provides direct job placement of the trainee. Earnings are increased through either increased weeks worked, reduced unemployment, or increased hours per week worked, full time instead of part time employment. The various types of training may have different effects on these dimensions versus wages.

OUTLINE

Section II considers issues that arise even when training is taken as predetermined. We first discuss a stylized model of the components of earnings in the context of panel data. Variables reflecting the various dimensions of training are then defined and introduced into the components of earnings. The FIML estimation procedure is developed for when training is exogenous. Finally, we discuss problems of misspecification that arise from failure to introduce the underlying complexity with respect to earnings components and training variables into the analysis.
In Section III we turn to the endogeneity of training and its potential relationships to pre-training earnings, given the dimensions of the model already developed. We begin by specifying the model relating training decisions to pre-training earnings components. Then we develop the reduced form earnings and training decision equations. We briefly discuss sources of potential specification error in the estimation procedure of Section II that treats training as exogenous. Next, we consider methods to estimate the parameters of the complete model with endogenous training decisions. We consider both multistage and full information estimation procedures. The stages of estimation in the multistage procedure presented help to motivate the identifying restrictions. Finally, FIML estimation is discussed through the specification of the likelihood for each type of training experience.
II. BEYOND PARTICIPATION EFFECTS ON EARNINGS: WITH EXOGENOUS TRAINING

Simple models relating participation in training to earnings contain several sources of potential misspecification or misinterpretation, even if participation in training is exogenous. These relate to some of the questions raised in the Introduction. What type of training was provided? Were these all participants or only those who completed the training? Did the program place individuals in jobs or did they find their own? How long did the effects of the training last? Did it primarily affect earnings through employment or wages, through reduced unemployment or reduced underemployment?

To clearly separate these issues from endogeneity, we begin by treating training as if it were predetermined and not correlated with the earnings residuals. In Sec. III we relax this assumption.

We are concerned with the role of the various components of earnings and with the underlying content and meaning of participation in training. We will go behind the scenes to consider the implications of a less aggregated analysis of the effect of participation on earnings. We consider issues of potential misspecification that may arise.

Subsequent sections rely heavily on the notation and models presented in this section.

THE EARNINGS EQUATIONS

We decompose annual earnings into its wage and employment components: average hourly wage rate (WAGE), annual weeks worked (WEEKS), and hours of work per week (HOURS). For individual i in period t,

\[ \text{LOGEARN}_{it} = \text{WAGE}_{it} + \text{WEEKS}_{it} + \text{HOURS}_{it} \]

where \( i = 1, N \) and \( t = 1, T \). We consider a logarithmic specification of earnings (LOGEARN) such that the components sum up to the total. This
decomposition of earnings is similar in spirit to those used in studies by Bassi et al. (1983); Dickinson, Johnson, and West (1984); and Lillard (1983, 1986). Longitudinal observations are assumed to cover both the pre-training and the post-training period and to be sufficiently long to identify all relevant parameters. Observations are assumed to be independent across individual workers but may be correlated over time as discussed below.

Following Ashenfelter and Card (1985), Hause (1980), Lillard and Weiss (1979), Lillard and Willis (1978), we include individual variance components. These studies include individual components in the earnings equation. We introduce individual components into each of the sources of earnings: WAGE, WEEKS, and HOURS. The model used here is a generalization of the dynamic labor supply model for wages and annual hours posed in Lillard (1983, 1986). Our earnings model views each worker as having his own individual life-cycle profile of wages with individual level (L) and growth (G) components and autoregressive transitory deviations over time (T).

The WAGE component represents the stock of human capital of the worker, which we interpret as reflecting productivity. This formulation allows for the systematic development of wages along individual life-cycle profiles, with stochastic variation away from the profile at any point in time.\(^1\) Log wage rate per hour:

\[
WAGE_{it} = WL_i + WG_i(t-t_0) + WT_{it}
\]

Level: \[WL_i = \alpha_iX_{iit} + \theta_iPGM_{it} + w_t\]

Growth: \[WG_i = \alpha_gX_{iit} + \theta_gPGM_{it} + w_g\]

Deviation: \[WT_{it} = \alpha_cX_{iit} + \theta_cPGMT_{it} + w_t\]

\(^1\)See Lillard and Weiss (1979) and Weiss and Lillard (1978) for a discussion of a model of human capital investment consistent with this specification and a discussion of experience vintage and time effects. Lillard (1983) finds that \(w_t\) is consistent with an ARMA process of fairly low order.
The implied wage profile need not be linear in time because WL and WG may depend functionally (say, in a quadratic way) on years of experience, full time experience, and so forth, which change over the life cycle. The time-varying variables $X_{it}$ include individual time variables. The residual deviation $w_t$ may be autoregressive. Participation in a training program may affect the level or growth rate of wages or it may have a more transitory effect.

The content of the vector of program participation variables represented by PGM and PGMT are given below. The PGM variables indicate a shift in the dependent variable because of training. They are time subscripted to indicate that the effect of the program applies only after it is taken. In addition to these permanent effects on the level and growth of earnings, some effects may be transitory and attenuate with time. The attenuation effects may be captured by introducing time since training, for example by $PGMT = PGM \times \exp(t_d - t)$. The training effects can be made to depend on other time-varying variables as well as on indicators of labor market demand through the use of further interactions.

The WEEKS and HOURS components represent labor supply. For pedagogical simplicity, we will simply specify these as reduced-form equations. This formulation allows for an individual mean level and stochastic variation around the long-run level.\(^2\) Log weeks worked per year:

$$WEEKS_{it} = WKL_i + WKT_{it}$$

Level: $WKL_i = \gamma_1 X_{4i} + \lambda_1 PGM_{it} + wkl_i$

Deviation: $WKT_{it} = \gamma_2 X_{5it} + \lambda_2 PGMT_{it} + wkt_{it}$

\(^2\)Lillard (1983, 1986) presents a fuller treatment of this model, where WEEKS and HOURS are combined into annual hours of work. The model includes a labor response to wage expectations. These articles include empirical estimates but do not consider training issues.
Log hours worked per week:

\[
\text{HOURS}_{it} = \text{HRL}_i + \text{HRT}_{it}
\]

**Level:**
\[
\text{HRL}_i = \beta_1 X_{6i} + \delta_1 \text{PGM}_{it} + hrl_i
\]

**Deviation:**
\[
\text{HRT}_{it} = \beta_2 X_{7it} + \delta_2 \text{PGMT}_{it} + hrt_{it}
\]

The mean levels represent permanent shifts in the labor supply of a worker. The time-varying components represent the effects of more transitory elements, such as local labor market demand conditions, illness, and so forth. All individual random components are assumed uncorrelated with measured variables X. Involuntary unemployment reduces WEEKS, and the inability to find full time work (underemployment) reduces HOURS. The training variables in each case may have either permanent or transitory effects.

The sources of earnings may be aggregated to earnings, resulting in the earnings function. The earnings function may be written to emphasize either the variance components or the effects of training.

\[
\text{LOGEARN}_{it} = (\alpha + \gamma + \beta) X_i + (\theta + \lambda + \delta) \text{PGM}_{it} + (\text{wl} + \text{wkl} + \text{hrl})_i
\]

**Level:**
\[
+ \alpha_1 X_i + \theta_1 \text{PGM}_{it} + \lambda_1 \text{PGMT}_{it} + \delta_1 \text{PGMT}_{it}
\]

**Growth:**
\[
+ (\alpha + \gamma + \beta) X_{it} + (\theta + \lambda + \delta) \text{PGM}_{it} + (\text{wl} + \text{wkl} + \text{hrl})_i
\]

**Deviation:**
\[
+ (\alpha + \gamma + \beta) X_{it} + (\theta + \lambda + \delta) \text{PGM}_{it} + (\text{wl} + \text{wkl} + \text{hrl})_i
\]

**Pre-Training:**
\[
= (\alpha + \gamma + \beta) X_i + (\alpha + \gamma + \beta) X_{it} + (\alpha + \gamma + \beta) X_{it}
\]

**Training Effect:**
\[
+ (\theta + \lambda + \delta) \text{PGM}_{it} + \theta_1 \text{PGM}_{it} + (\theta + \lambda + \delta) \text{PGM}_{it} + (\theta + \lambda + \delta) \text{PGMT}_{it}
\]

**Residual:**
\[
+ (\text{wl} + \text{wkl} + \text{hrl})_i + \text{wgt}(t-t_0) + (\text{wl} + \text{wkl} + \text{hrl})_i
\]

\footnote{Lillard and Tan (1986) find that private sector training has the effect of reducing the probability of unemployment as well as enhancing earnings.}
THE TRAINING VARIABLES

The following is an illustrative set of variables reflecting the character of the training experience of a worker. First, a worker either participates in the program or does not, that is,

\[
\text{TRN}_i = \begin{cases} 
1 & \text{if participates in training} \\
0 & \text{if not}
\end{cases}
\]

Given participation in the program, an individual is assigned to a particular training subprogram type. CETA had three subprograms, which we denote by the following indicator variables:

\[
\text{CLS}_i = \begin{cases} 
1 & \text{if in classroom training} \\
0 & \text{Otherwise}
\end{cases}
\]

\[
\text{OJT}_i = \begin{cases} 
1 & \text{if in on-the-job training} \\
0 & \text{Otherwise}
\end{cases}
\]

\[
\text{PSE}_i = \begin{cases} 
1 & \text{if in public service employment} \\
0 & \text{Otherwise}
\end{cases}
\]

*The set of training variables defined here is applicable to the characteristics of CETA training programs. The variables are illustrative in the sense that further detail about CETA program characteristics could be introduced and other training programs would have a different set of characteristics, subprograms, and decision processes.*
The types of training are quite different from one another so that the effects on earnings may be quite different.

A participant in the training program may complete the program of training, that is,

$$CMPL_4 = \begin{cases} 
1 & \text{if complete training} \\
0 & \text{if not}
\end{cases}$$

The effect of the training program may be reduced or negated if the program is not completed.

Finally, some of those workers completing the program are placed in jobs and, as a result, indicate this by

$$JOB_4 = \begin{cases} 
1 & \text{if placed in a job after training} \\
0 & \text{if not}
\end{cases}$$

Next, consider the specification of the potential effects of these training "participation" variables on wages, hours, and weeks, and thus on earnings. First, participation per se has no direct effect on earnings; only the type of subprogram actually attended has an effect. In addition, the effect of not completing the training may be captured by an interaction of CMPL with program type—e.g. CMPL × OJT. Similarly, the effect of job placement may differ by program type and may be captured by interactions of program type with JOB. The resulting set of variables contained in the vector PGM are

$$PGM' = (CLS, OJT, PSE, CMPL × CLS, CMPL × OJT, CMPL × PSE, JOB × CLS, JOB × OJT, JOB × PSE) .$$
As noted earlier, we specify \( \text{FGMT}_{it} = \text{PGM}_{i} \times \exp(t_{d} - t) \) to introduce potential deterioration in the effect of training.

The wage, hours per week, and weeks equations may be written in terms of the full set of training variables as follows:

\[
\begin{align*}
\text{WAGE}_{it} &= \alpha_{1} X_{3i} + \alpha_{2} X_{2i} + \alpha_{3} X_{3it} \\
&+ \theta_{11}\text{CLS}_{i} + \theta_{12}\text{OJT}_{1} + \theta_{13}\text{PSE}_{i} \\
&+ \theta_{14}\text{CMPL} \times \text{CLS}_{i} + \theta_{15}\text{CMPL} \times \text{OJT}_{1} + \theta_{16}\text{CMPL} \times \text{PSE}_{i} \\
&+ \theta_{17}\text{JOB} \times \text{CLS}_{i} + \theta_{18}\text{JOB} \times \text{OJT}_{1} + \theta_{19}\text{JOB} \times \text{PSE}_{i} \\
&+ \theta_{21}\text{CLS}_{i}(t-t_{0}) + \theta_{22}\text{OJT}_{1}(t-t_{0}) + \theta_{23}\text{PSE}_{i}(t-t_{0}) \\
&+ \theta_{24}\text{CMPL} \times \text{CLS}_{i}(t-t_{0}) + \theta_{25}\text{CMPL} \times \text{OJT}_{1}(t-t_{0}) + \theta_{26}\text{CMPL} \times \text{PSE}_{i}(t-t_{0}) \\
&+ \theta_{31}\text{JOB} \times \text{CLS}_{i}(t-t_{0}) + \theta_{32}\text{JOB} \times \text{OJT}_{1}(t-t_{0}) + \theta_{33}\text{JOB} \times \text{PSE}_{i}(t-t_{0}) \\
&+ \theta_{41}\text{CLS}_{i} \times \exp(t_{d} - t) + \theta_{42}\text{OJT}_{1} \times \exp(t_{d} - t) + \theta_{43}\text{PSE}_{i} \times \exp(t_{d} - t) \\
&+ \theta_{44}\text{CMPL} \times \text{CLS}_{i} \times \exp(t_{d} - t) + \theta_{45}\text{CMPL} \times \text{OJT}_{1} \times \exp(t_{d} - t) \\
&+ \theta_{46}\text{CMPL} \times \text{PSE}_{i} \times \exp(t_{d} - t) \\
&+ \theta_{71}\text{JOB} \times \text{CLS}_{i} \times \exp(t_{d} - t) + \theta_{72}\text{JOB} \times \text{OJT}_{1} \times \exp(t_{d} - t) \\
&+ \theta_{73}\text{JOB} \times \text{PSE}_{i} \times \exp(t_{d} - t) \\
&+ \text{wl}_{i} + \text{wg}_{i} + \text{wt}_{it}
\end{align*}
\]

\[
\begin{align*}
\text{WEEKS}_{it} &= \gamma_{1} X_{3i} + \gamma_{2} X_{3it} \\
&+ \lambda_{11}\text{CLS}_{i} + \lambda_{12}\text{OJT}_{1} + \lambda_{13}\text{PSE}_{i} \\
&+ \lambda_{14}\text{CMPL} \times \text{CLS}_{i} + \lambda_{15}\text{CMPL} \times \text{OJT}_{1} + \lambda_{16}\text{CMPL} \times \text{PSE}_{i} \\
&+ \lambda_{17}\text{JOB} \times \text{CLS}_{i} + \lambda_{18}\text{JOB} \times \text{OJT}_{1} + \lambda_{19}\text{JOB} \times \text{PSE}_{i} \\
&+ \lambda_{21}\text{CLS}_{i} \times \exp(t_{d} - t) + \lambda_{22}\text{OJT}_{1} \times \exp(t_{d} - t) + \lambda_{23}\text{PSE}_{i} \times \exp(t_{d} - t) \\
&+ \lambda_{24}\text{CMPL} \times \text{CLS}_{i} \times \exp(t_{d} - t) + \lambda_{25}\text{CMPL} \times \text{OJT}_{1} \times \exp(t_{d} - t) \\
&+ \lambda_{26}\text{CMPL} \times \text{PSE}_{i} \times \exp(t_{d} - t) \\
&+ \lambda_{71}\text{JOB} \times \text{CLS}_{i} \times \exp(t_{d} - t) + \lambda_{72}\text{JOB} \times \text{OJT}_{1} \times \exp(t_{d} - t) \\
&+ \lambda_{73}\text{JOB} \times \text{PSE}_{i} \times \exp(t_{d} - t) \\
&+ \text{wk}_{i} + \text{wt}_{it}
\end{align*}
\]
\[ \text{HOURS}_{it} = \beta_1 X_{i1} + \beta_2 X_{i2} \]
\[ + \delta_{11}\text{CLS}_i + \delta_{12}\text{OJT}_i + \delta_{13}\text{PSE}_i \]
\[ + \delta_{14}\text{CMPL} \times \text{CLS}_i + \delta_{15}\text{CMPL} \times \text{OJT}_i + \delta_{16}\text{CMPL} \times \text{PSE}_i \]
\[ + \delta_{17}\text{JOB} \times \text{CLS}_i + \delta_{18}\text{JOB} \times \text{OJT}_i + \delta_{19}\text{JOB} \times \text{PSE}_i \]
\[ + \delta_{14}\text{CMPL} \times \text{exp}(t_d - t) + \delta_{15}\text{OJT} \times \text{exp}(t_d - t) + \lambda_{\text{PSE}} \text{PSE}_i \times \text{exp}(t_d - t) \]
\[ + \delta_{14}\text{CMPL} \times \text{CLS}_i \times \text{exp}(t_d - t) + \delta_{15}\text{CMPL} \times \text{OJT}_i \times \text{exp}(t_d - t) \]
\[ + \delta_{16}\text{CMPL} \times \text{PSE}_i \times \text{exp}(t_d - t) \]
\[ + \delta_{17}\text{JOB} \times \text{CLS}_i \times \text{exp}(t_d - t) + \delta_{18}\text{JOB} \times \text{OJT}_i \times \text{exp}(t_d - t) \]
\[ + \delta_{19}\text{JOB} \times \text{PSE}_i \times \text{exp}(t_d - t) \]
\[ + \hat{w}_{kl} + w_{it} \]

Recall that the training indicator variables are turned on only after the period of training.

**ESTIMATION OF PARAMETERS WITH TRAINING EXOGENOUS**

In this subsection we discuss procedures to be used to estimate the parameters of the processes for WAGES, WEEKS, and HOURS when training is taken to be predetermined.

Define \( Y \) to be the \((3T \times 1)\) vector of observable variables

\[ Y' = [\text{WAGE}', \text{WEEKS}', \text{HOURS}'] \]

Order the time-series vector of observations on each of the observed dependent variables so that the \( T_0 \) pre-training values (denoted by 0) are followed by the \( T_1 \) post-training values (denoted 1), where \( T = T_0 + T_1 \) is the length of the panel.
These observable variables are related to the individual and time-varying components, ERN. The entities within ERN are also ordered so that the pre-training values come first.

\[ \text{ERN}' = (\text{ERN}_0, \text{ERN}_1) \]  \hspace{1cm} (2.4)  

where \( \text{ERN}_0 = (W_L_0, W_G_0, W_K_0, H_R_0, W_T_0, W_K_T_0, H_R_T_0) \).  
and \( \text{ERN}_1 = (\Delta W_L, \Delta W_G, \Delta W_T, \Delta W_K, \Delta H_R, \Delta H_R_T, W_T', W_K_T', H_R_T') \).

The elements in \( \text{ERN}_0 \) are ordered so that individual components are followed by time-varying ones. The elements in \( \text{ERN}_1 \) include changes in the individual components, the attenuating effects, that are due to training, and post-training time-varying values. The pre-training values of individual components carry forward into the post-training period, as reflected in the relationship of measured variables to the elements of ERN.

The observable variables \( Y \) map into the underlying latent variables, the elements of ERN, according to the measurement equation.

\[ Y = \Lambda_y \text{ERN} \]

where

\[
\Lambda_y = \begin{bmatrix}
1 & (t-t_0) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & (t-t_0) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

is \((3T \times (3T + 1))\).
and where \( \mathbf{1} \) is a column vector of ones, \( \mathbf{I} \) is the identity matrix, \((t-t_0)\) is a vector of time deviations from some base period \( t_0 \), and \((t-t_d)\) is the time deviation from the training period \( t_d \). The first row yields the pre-training time series of WAGE values, including the individual components and pre-training transitory components. The second row yields the post-training time series of WAGE values, including the individual components, the changes due to training, and post-training transitory components. The other observable variables, HOURS and WEEKS, are similar except that the individual growth component is omitted.

The individual and time-varying components of ERN are related to the measured variables \( \mathbf{X} \), including \( \mathbf{PGM} \), by the equation

\[
\text{ERN} = \Gamma_{x} \mathbf{X} + \xi
\]

where the measured variables are

\[
\mathbf{X}' = [\mathbf{X}', \mathbf{PGM}', \mathbf{X}_{T_0}, \ldots, \mathbf{X}_{T_1}, \ldots, \mathbf{X}_{T_{T1}}]
\]

where again \( T_0 \) and \( T_1 \) are the number of pre- and post-training periods respectively. The regression coefficient matrix \( \Gamma_x \) is defined as follows.

\[
\Gamma_x = \begin{bmatrix}
\Gamma_0 \\
\Gamma_1
\end{bmatrix}
\]

\[
\begin{bmatrix}
\alpha_1' & 0 & 0 & 0 \\
\alpha_g' & 0 & 0 & 0 \\
\gamma_1' & 0 & 0 & 0 \\
\beta_1' & 0 & 0 & 0 \\
0 & 0 & \mathbf{I} \otimes \alpha_r' & 0 \\
0 & 0 & \mathbf{I} \otimes \gamma_r' & 0 \\
0 & 0 & \mathbf{I} \otimes \beta_r' & 0 \\
0 & 0 & 0 & \mathbf{I} \otimes \alpha_r' \\
0 & 0 & 0 & \mathbf{I} \otimes \gamma_r' \\
0 & 0 & 0 & \mathbf{I} \otimes \beta_r'
\end{bmatrix}
\]
The resulting regression equation in terms of measured variables and residuals is

\[ Y = \Lambda_y \Gamma_x X + \Lambda_y \xi \].

The coefficients may be consistently estimated by OLS, pooling observations over time for each earnings component, WAGES, WEEKS, and HOURS and including appropriate variables and interaction terms. Because of heteroscedasticity and correlation of errors over time, standard errors reported by OLS procedures will be incorrect.

The individual and time-varying residual terms in \( \xi \) are ordered the same as in ERN.

\[
\begin{align*}
\xi &= (\xi_0, \xi_t) \\
\xi_0 &= (W_{l0}, W_{g0}, W_{l0}, W_{h0}, W_{t0}, W_{k0}, W_{h0}) \\
\xi_t &= (0, 0, 0, 0, 0, 0, 0, W_{t}, W_{k}, W_{h})
\end{align*}
\]

All residual terms are assumed to be jointly normal with zero mean. The individual components and the time-varying components are uncorrelated. The first seven terms of \( \xi_t \) are zero, and have zero variance. These terms are introduced simply to allow the training variables PGM to affect only post-training values and to separate the pre-training values ERN_0 in a way that will be convenient in the next section where training is endogenous. Efficient FIML estimates and correct standard errors may be obtained by maximum likelihood methods. The log likelihood function is given by

\[
\ln L = -(N/2) \left[ \ln(\Lambda_y \Sigma \xi \Lambda_y') \right] \\
+ \text{tr} \left[ \left( \Lambda_y \Sigma \xi \Lambda_y' \right)^{-1} \left( S_{yy} - \Lambda_y \Gamma_x \Gamma_p \begin{bmatrix} S_{xx} \\ S_{px} \end{bmatrix} - \left[ S_{xx} \begin{bmatrix} \Gamma_x' \\ \Gamma_p \end{bmatrix} \right] \Lambda_y' \right] \\
+ \Lambda_y \Gamma_x \Gamma_p \begin{bmatrix} S_{xx} & S_{xp} \\ S_{px} & S_{pp} \end{bmatrix} \begin{bmatrix} \Gamma_x' \\ \Gamma_p' \end{bmatrix} \Lambda_y' \right] \]
assuming joint normality of the residual terms $\xi$. The residual covariance matrix $E_{\xi\xi}$ is constructed such that individual components may be freely correlated, but are uncorrelated with time-varying components. The three time components are uncorrelated ARMA processes.\footnote{The ARMA processes may be correlated if structural relationships are introduced between components. See Lillard (1983). Higher order ARMA processes require more periods of observation for identification.}

The only restrictions placed on the model, aside from the exogeneity of training, are that the individual and time-varying residual components be uncorrelated. Any structural relationships introduced between WEEKS or HOURS and the wage rate will necessitate additional restrictions. Implicit restrictions are that the length of the time series $T$ is long enough so that all variance component and autoregressive parameters are identified and that the measured variables $X$ and $PGM$ are independent of the residual terms.

**THE POTENTIAL FOR MISSPECIFICATION EVEN WITH TRAINING EXOGENOUS**

Here we consider several common empirical specifications in the context of this model.

Some basic features are common to each equation. The nine training variables potentially affect the level, the growth rate (in the case of wages), and the time pattern (in the form of effects that attenuate over time) of each of the components of earnings. Therefore, the estimated effect of a training program or any aspect of it may vary with the amount of time since the training was taken, $t - t_d$. Lillard and Tan (1986) find evidence of attenuation in the earnings or wage effects of more general types of training, as well as in the effects on employment prospects.

For any of the components of earnings, failure to completely specify the training variables will lead to a confounding of effects and possibly unstable estimated effects if the underlying proportions getting various forms of training vary.
Consider a regression of weeks worked on TRN, the indicator variable for participation in a training program. For simplicity, consider the case where the training effects do not attenuate with time, $\lambda^*_t = 0$.

$$\text{WEEKS}_{it} = \gamma^*_1 X_{it1} + \gamma^*_r X_{3it} + \lambda_{trn} TRN_{it} + wkl_i + wkt_{it}$$

The estimated effect, $\lambda_{trn}$, has an expectation that is the average of the effects of the various possible training experiences (program activity, completion, and placement) weighted by the proportion of trainees in each category.

$$E(\lambda_{trn}) = (f_1\lambda_{11} CLS_i + f_2\lambda_{12} OJT_i + f_3\lambda_{13} PSE_i + f_4\lambda_{14} CMPL \times CLS_i + f_5\lambda_{15} CMPL \times OJT_i + f_6\lambda_{16} CMPL \times PSE_i + f_7\lambda_{17} JOB \times CLS_i + f_8\lambda_{18} JOB \times OJT_i + f_9\lambda_{19} JOB \times PSE_i) / \left(\sum_{i=1}^{g} f_i\right)$$

where $f$ is the proportion of trainees in a particular designated category.

Similarly, regression of weeks worked on an indicator variable for completion of a training program, CMPL, will give the difference between the weighted mean for all completers and the weighted mean for nonparticipants and noncompleters.

$$\text{WEEKS}_{it} = \gamma^*_1 X_{it1} + \gamma^*_r X_{3it} + \lambda_{cmp} CMPL_{it} + wkl_i + wkt_{it}$$

$$E(\lambda_{cmp}) = (f_1\lambda_{14} CMPL \times CLS_i + f_2\lambda_{15} CMPL \times OJT_i + f_3\lambda_{16} CMPL \times PSE_i + f_4\lambda_{17} JOB \times CLS_i + f_5\lambda_{18} JOB \times OJT_i + f_6\lambda_{19} JOB \times PSE_i) / \left(\sum_{i=1}^{g} f_i\right) - (f_1\lambda_{11} CLS_i + f_2\lambda_{12} OJT_i + f_3\lambda_{13} PSE_i) / (f_1 + f_2 + f_3)$$
Even a similar regression equation for those trainees in the OJT program and nonparticipant controls will confound the effects of job placement. The basic point is that training programs are complex, and failure to properly control for the relevant training variables leads to a confounding of the true effects and parameter instability.

When the aggregate earnings variable is considered, the wage, weeks, and hours components are confounded and cannot be distinguished. Therefore, the problems of misspecification are even more prominent. A regression of earnings on an indicator variable for either participation in or completion of a training program confounds many potential training effects.

\[
\text{LOGEARN}_{it} = (\alpha + \gamma + \beta_i)X_i + \alpha_0X_i(t-t_0) + (\alpha + \gamma + \beta_i)X_i \\
+ (\theta + \lambda + \delta_i)\text{PGM}_{it} + \theta_0\text{PGM}_{it}(t-t_0) + (\theta + \lambda + \delta_i)\text{PGMT}_{it} \\
+ (wl + wkl + hrl)_{it} + wg_i(t-t_0) + (wt + wkt + hrt)_{it}
\]

This suggests that previous applications of econometric methods designed to deal with earnings and the endogeneity of participation may have been oversimplified.
III. ENDOGENOUS SELF-SELECTION AND PRIME SPONSOR DECISIONS

In this section, we turn to the endogeneity of training and its potential relationships to pre-training earnings, given the dimensions of the model developed in the last section. We first specify the model relating training decisions to pre-training earnings components. Then we develop the reduced form earnings and training decision equations. We briefly discuss sources of potential specification error in the estimation procedure of Sec. II that treats training as exogenous. Next, we consider methods to estimate the parameters of the complete model with endogenous training decisions. We consider both multistage and full information estimation procedures. The stages of estimation in the multistage procedure presented help to motivate the identifying restrictions. Next, we discuss FIML estimation through the specification of the likelihood for each type of training experience.

For expository clarity, we drop the i subscripts in this section. The following discussion assumes that the full panel of data on WAGES, WEEKS, and HOURS is available for each observation.

THE ENDOGENEITY OF TRAINING DECISIONS

It is widely recognized that participation in training is not exogenous. However, the literature on estimation methods has ignored the complexity of training decisions, all of which may be endogenous, whereas the evaluation literature has emphasized it. In this section we consider a stylized version of training decisions.

Because pre-training earnings may affect the various training decisions, as is frequently noted in the literature, we include the various components of earnings for pre-training periods in the vector \( E_R^0 \). Recall from Eq. (2.4) that

\[
E_R^0 = (WL_0, WG_0, WKL_0, HRL_0, WT^*_0, WKT^*_0, HRT^*_0) .
\]
The WT, WKT, and HRT are (T₀×1) vectors. Not all past values of transitory variables need be important—e.g., it may be that only WKTₜ₋₁ and WKTₜ₋₂ have an effect. The model uses the temporal ordering of training events and decisions in its structural representation. Pre-training earnings and its components are predetermined at the time of the training decisions and may influence those decisions. After the training period, those decisions are given and have their effects on the components of earnings. The casual relationships are thus triangular (recursive, but not independent).

This approach is similar to the one used in Ashenfelter and Card (1985) except that this approach examines the source of low earnings—weeks worked, hours per week, or wage rate—and it allows for the complexity of the training decisions. Participation in training, in particular, is likely to be related to weeks worked because CETA is designed to aid the unemployed as well as educationally or economically disadvantaged workers.

The training decisions are essentially sequential. First, an eligible individual must decide to participate in a training program. Then a participating individual is assigned to a particular type of program (called "program activity"), taken here to be classroom training (CLS), on-the-job training (OJT), or public service employment (PSE), based on what the local prime sponsor believes will be best for that person. We take these to be ordered in an underlying dimension related to the individual's work record. Given assignment to a program activity, the person will either complete the program of training or not. This decision is made by the individual on the basis of a revised estimate of the benefits and costs of training. Finally, among those completing the training program, some will be placed in jobs (by the prime sponsor) and others will not.

**Participation**

A worker in some period tₚ must decide whether to participate in a CETA training program. Define an indicator variable for program participation TRN to depend on an underlying equation for the "propensity to participate," Aₚ:p,

\[
TRN = \begin{cases} 
1 & \text{iff } Aₚ > 0 \\
0 & \text{Otherwise} 
\end{cases}
\]
where the propensity to participate is related to pre-training earnings components and worker characteristics \( Z \).

\[
A_p = \gamma_p Z + \chi_p \text{ERN}_0 + u_p
\]  

(3.2)

The vector of regressors \( Z \) includes variables reflecting the cost of training and its benefits (including benefits other than earnings). Pre-training earnings components appear in \( \text{ERN}_0 \). Assuming normality of \( u_p \) and an appropriate normalization such as \( \sigma_{u_p} = 1 \), this is a probit specification.

**Program Assignment**

Given participation in the training program, a person is assigned to a particular program activity. These activities are not assigned at random but, as noted by Westat (1982), according to the prime sponsor's notion of the person's employability, which we denote as \( E \). Greater employability is required to move from classroom training CLS to on-the-job training OJT or to public service employment PSE. This ordering of the program activities leads naturally\(^1\) to the ordered probit model.

Let CLS, OJT, and PSE denote appropriate indicator variables. The choice of activity is then defined by

\[
\text{CLS} = \begin{cases} 
1 & \text{iff } E < 0 \\
0 & \text{Otherwise}
\end{cases}
\]  

(3.3)

\[
\text{OJT} = \begin{cases} 
1 & \text{iff } 0 < E < E^* \\
0 & \text{Otherwise}
\end{cases}
\]  

(3.4)

\[
\text{PSE} = \begin{cases} 
1 & \text{iff } E > E^* \\
0 & \text{Otherwise}
\end{cases}
\]  

(3.5)

\(^1\)The ordering of choices is not essential to the main point of the Note. They may be made to be unordered choices.
where the first threshold value is normalized to zero, the second threshold value \( E^* \) is to be estimated, and \( \sigma_{ua} = 1 \).

The employability variable determining program placement is a function of explanatory variables \( Z \) and \( ERN_0 \),

\[
E = \xi^*_Z + \chi^*_Z ERN_0 + ua
\]  

(3.6)

which reflect the judgment of the prime sponsor as to the best program for the person based on his employment history--to the extent that it is reflected in the trainee's application form and thus available to the program sponsor--and based on the prime sponsor's knowledge of the local labor market environment.

**Completion of Training**

As participants proceed through the training associated with their program assignment, they learn more about the possible benefits and costs of the program, and their circumstances change. Some persons may learn that the training will not enhance their earnings as much as expected or that it will not necessarily get them a job in the end. The new assessment may be that the training is not worthwhile. Other persons may find a better job during the course of the training period. The basic notion is that changes in the expected benefits or costs of the program represent an added independent disturbance (with zero mean) to the initial propensity to participate.

The propensity to complete the training program is the original propensity to participate plus an added source of variation uncorrelated with all other residual terms.

\[
Ac = Ap + uc
\]

\[
= \xi^*_pZ + \chi^*_pERN_0 + up + uc
\]
The program completion indicator variable is defined as follows:

$$\text{CMPL} = \begin{cases} 1 \text{ iff } A_c > 0 \\ 0 \text{ Otherwise} \end{cases}$$

The added variance of uc (estimated as $\sigma_{uc}$) induces some participants to drop out when $A_c < 0$. The share of participants who subsequently drop out adds information about the variability of new information relative to initial assessments. To drop out of training is a choice of the participant and represents a change of circumstances. That change should be uncorrelated with the original $A_p$, but the residual terms contain a common term (up) so that the choices are correlated conditional on measured variables.

It may be desirable to introduce measures reflecting changes (say) in local labor market conditions into the equation. Improved economic conditions may lead to employment opportunities outside the CETA setting before the training program is complete. There is some evidence in Dickinson, Johnson, and West (1984) that adult males are more likely to leave early and that the earnings gains to them are consistently negative, especially for OJT. This may simply reflect the better trainees getting jobs and leaving the program.

Job Placement

Some workers who complete their training program are placed in jobs by their local prime sponsor, while others are not. Define the indicator variable for job placement as follows.

$$\text{JOB} = \begin{cases} 1 \text{ iff } A_j > 0 \\ 0 \text{ Otherwise} \end{cases}$$
The propensity to be placed in a job upon completion of training is again a function of measured variables $Z$ and pre-training earning components.

$$Aj = \xi_j^* Z + \chi_j^* \text{ERN}_0 + u_j$$

The degree of placement may vary greatly among local prime sponsors depending on the administration of the program, contacts with employers, and the state of local labor demand. Placement in a job at the completion of training may depend as well on the type of training received. For example, those in PSE may be more likely to retain similar jobs after training, and those in OJT may have some possibility of employment with a firm where they train (this is sometimes cited as a goal), but those in classroom training have far fewer similar possibilities. Several evaluation studies have cited the tendency for trainees to end up employed in public service jobs after completion of training. This possibility is not included here but could be introduced easily.

**REDUCED FORM EARNINGS AND TRAINING CHOICE EQUATIONS**

At this point it is convenient to draw together the several equations of the model and write them in reduced form. Recall that the panel time-series of the values of WAGES, WEEKS, and HOURS in Sec. II were written as

$$Y = \Lambda_\nu \text{ERN}$$

where

$$\text{ERN} = \Gamma_\nu X + \xi$$
so that

\[ Y = \Lambda_\gamma \Gamma_2 X + \Lambda_\gamma \xi . \]

The components of ERN can be partitioned into those elements involved in the pre-training period and those that are not.

\[
\begin{bmatrix}
\text{ERN}_0 \\
\text{ERN}_1
\end{bmatrix} = \begin{bmatrix}
\Gamma_0 \\
\Gamma_1
\end{bmatrix} X + \begin{bmatrix}
\xi_0 \\
\xi_1
\end{bmatrix}
\]

The structural equations for the training choices may be written as

\[
\begin{bmatrix}
A_p \\
E \\
A_c \\
A_j
\end{bmatrix} = \begin{bmatrix}
\xi'_{p} \\
\xi'_{a} \\
\xi'_{p} \\
\xi'_{j}
\end{bmatrix} Z + \begin{bmatrix}
x'_p \\
x'_a \\
x'_p \\
x'_j
\end{bmatrix} \text{ERN}_0 + \begin{bmatrix}
\text{up} \\
\text{ua} \\
\text{up + uc} \\
\text{uj}
\end{bmatrix}
\]

or in reduced form

\[
\begin{bmatrix}
A_p \\
E \\
A_c \\
A_j
\end{bmatrix} = \begin{bmatrix}
\xi'_{p} \\
\xi'_{a} \\
\xi'_{p} \\
\xi'_{j}
\end{bmatrix} Z + \begin{bmatrix}
x'_p \\
x'_a \\
x'_p \\
x'_j
\end{bmatrix} \Gamma_0 X + \begin{bmatrix}
\text{up} \\
\text{ua} \\
\text{up + uc} \\
\text{uj}
\end{bmatrix} + \begin{bmatrix}
x'_p \\
x'_a \\
x'_p \\
x'_j
\end{bmatrix} \xi_0
\]

where the last two terms make up the reduced form residuals for the training choice equations.
To obtain the covariance matrix for the reduced form residuals, first consider the covariance of the structural residuals from the choice equations (distinguishing up and uc) and from the earning component equations ERN.

\[
\Sigma_s - V = \begin{bmatrix}
\Sigma_{uu} & \Sigma_{ua} & \Sigma_{uc} & \Sigma_{uj} & \Sigma_{u\xi_0} & \Sigma_{u\xi_1} \\
\Sigma_{au} & 1 & 0 & 0 & 0 & 0 \\
\Sigma_{ac} & 0 & 1 & 0 & 0 & 0 \\
\Sigma_{aj} & 0 & 0 & 1 & 0 & 0 \\
\Sigma_{\xi_0} & 0 & 0 & 0 & 1 & 0 \\
\Sigma_{\xi_1} & 0 & 0 & 0 & 0 & 1 
\end{bmatrix}
\]

The training choice residuals may be correlated only with individual components from the earnings equations, and not time varying residual components.

The reduced reform residuals are obtained from the structural residuals by the transformation matrix

\[
B_r = \begin{bmatrix}
1, 0, 0, 0, \chi_p, 0 \\
0, 1, 0, 0, \chi_s, 0 \\
1, 0, 1, 0, \chi_p, 0 \\
0, 0, 0, 1, \chi_p, 0 \\
0, 0, 0, 0, \Lambda_y 
\end{bmatrix}
\]

so that the reduced covariance matrix is \( R = B_r \Sigma B_r' \).

**SOURCES OF SPECIFICATION ERROR**

The endogeneity of the training decisions and the potential effects of pre-training earnings components on those training decisions introduce potential sources of specification error if they are not properly controlled. These sources are in addition to the sources discussed in Sec. II. Even if correctly specified in terms of the earnings components and training variables, the estimation procedure
outlined in Sec. II will not provide consistent estimates because the error terms are not uncorrelated with the training variables.

Specification error due to failure to control for the endogeneity of the qualitative training variables is similar to that of the well-known case of a single endogenous binary variable in a single equation regression model. It is different because the vectors of training variables PGM are all jointly endogenous and interrelated. Second, several interrelated regression equations—for WAGES, HOURS, and WEEKS—each are functions of the training variables. Third, the endogeneity occurs in the context of panel data on each of these equations.

Let us assume that the regression equations for WAGES, HOURS, and WEEKS and the training variables are correctly specified so that the residual vector for any given observation is \( A_y \xi \). Estimates of the WAGES, HOURS, and WEEKS equations alone will be inconsistent because the training variables are correlated with the residuals of these equations. The correlation may arise from several sources. The training decisions may depend directly on pre-training values of the dependent variables, WAGES, HOURS, and WEEKS. Because the individual components in \( \xi_0 \) are present in the WAGES, HOURS, and WEEKS equations both before and after training, this introduces an indirect source of correlation that carries forward to the post-training period. The residuals in the training choice equations may be directly correlated with \( \xi_0 \), which enters both pre-training and post-training equations.

The expected values of the residuals of the WAGES, HOURS, and WEEKS equations conditional on regressors and the training variables will not be zero. The expectation will be a complicated function of the expectations of the training choice variables conditional on the qualitative range of those variables that leads to the training combination chosen.

A MULTISTAGE ESTIMATION PROCEDURE

This procedure builds a full set of parameter estimates in stages. The first set estimates reduced parameters of the training choice equations using the sequential probit model. Parameter restrictions are necessary for identification if the choices are structurally related to
pre-training earning components \( \text{ERN}_0 \) or the structural residuals are correlated.

**Stage 1: Pre-training Components of Wages, Hours, and Weeks**

Using only the pre-training sample observations for all individuals, both those receiving training and those not, the parameters of the regression equations \( \Gamma_0 \) and residual covariance structure \( \Sigma_0 \xi_0 \xi_0 \) for the components of \( \text{ERN}_0 \) may be estimated using the procedure developed in Sec. II. These parameter estimates may be used to construct an instrument for \( \text{ERN}_0, \Gamma_0 X \), to be used in subsequent stages.

**Stage 2: Participation Equation Parameters**

The parameters of the participation choice equation can be estimated in either structural or reduced form by a probit model. From the definition of TRN above we know that

\[
\text{TRN} = 0 \implies \text{up} + \chi' \xi_0 \leq - (\tau' \xi Z + \chi' \Gamma_0 X)
\]

and

\[
\text{TRN} = 1 \implies \text{up} + \chi' \xi_0 > - (\tau' \xi Z + \chi' \Gamma_0 X).
\]

The likelihood conditional on \( X \) is given by

\[
\text{Prob(} \text{TRN} | X \text{)} = \Phi[-(1 - 2 \cdot \text{TRN}) \cdot (\tau' \xi Z + \chi' \Gamma_0 X)/r_1]
\]

where \( \Phi \) denotes the cumulative normal probability (probit) function of appropriate dimension, and \( r_1 \) is the square root of \( r_{11} \), which is the first diagonal element of the reduced form covariance matrix \( R = \{r_{ij}\} = B \Sigma B' \) defined above. The reduced form coefficients are estimated relative to the reduced form residual standard deviation. Direct
application of this likelihood form with all variables $X$ and $Z$ included gives reduced form estimates.

Given consistent estimates of the earning component regression parameters from stage 1, instruments for the components of $\text{ERN}_0$ may be computed based on the estimated values of $\Gamma_X$, that is,

$$\text{ERN}_0 = \Gamma_X X_0$$

where $X_0$ denotes the values for the pre-training period. For these to be valid instruments and for these parameters to be identified there must be at least one variable affecting each component of $\text{ERN}_0$--in $X_0$--but not directly affecting the participation decision. These structural probit equations provide estimates of $\zeta_P$ and $x_P$ as well as the covariance terms $\Sigma_{0\text{up}}$.

Stage 3: Sub-program Assignment Equation Parameters

The parameters of the reduced form program assignment equation can be estimated using the second stage of a bivariate sequential probit model.

The first stage is the participation decision. The reduced form participation equation parameters are identified without further restrictions. However, identification of the reduced form coefficients for the program assignment equation relative to the residual standard deviation and the correlation between it and the participation assignment equation require further coefficient restrictions.

From the definition of CLS, OJT and PSE above we know that

$$\begin{align*}
\text{CLS} - 1 & \Rightarrow \quad U_a X_a^0 \leq (\zeta_a' Z + x_a' \Gamma_0 X) \\
\text{OJT} - 1 & \Rightarrow \quad -(\zeta_a' Z + x_a' \Gamma_0 X) < U_a + x_a' x_0 \leq E^* - (\zeta_a' Z + x_a' \Gamma_0 X) \\
\text{PSE} - 1 & \Rightarrow \quad E^* - (\zeta_a' Z + x_a' \Gamma_0 X) < U_a + x_a' x_0 \leq E^* - (\zeta_a' Z + x_a' \Gamma_0 X)
\end{align*}$$
The likelihood of participation and assignment to each of the three programs is given by

\[
\begin{align*}
\text{Prob}(\text{TRN} = 1, \text{CLS} = 1|\text{X}) &= \Phi\left[\left(\zeta_p Z + \chi_p \Gamma_0 \text{X}\right)/r_1, \right. \\
&\quad \left. -\left(\zeta_a Z + \chi_a \Gamma_0 \text{X}\right)/r_2 \right]/r_2] \\
\text{Prob}(\text{TRN} = 1, \text{OJT} = 1|\text{X}) &= \Phi\left[\left(\zeta_p Z + \chi_p \Gamma_0 \text{X}\right)/r_1, \right. \\
&\quad \left. \times(E^* - \left(\zeta_a Z + \chi_a \Gamma_0 \text{X}\right)/r_2 \right]/r_2] \\
\text{Prob}(\text{TRN} = 1, \text{PSE} = 1|\text{X}) &= \Phi\left[\left(\zeta_p Z + \chi_p \Gamma_0 \text{X}\right)/r_1, \right. \\
&\quad \left. -\left(\zeta_a Z + \chi_a \Gamma_0 \text{X}\right)/r_2 \right]/r_2]
\end{align*}
\]

where the symmetry of the bivariate normal has been invoked to allow the use of the cumulative normals.

To see the identification issue, note that conditional on \text{X}, the information on program assignment adds only two independent proportions because the four add up to 1. The participation proportion subdivides into the three proportions of participants in each program. However, three additional parameters are added, (1) the regression value conditional on \text{X}, (2) the threshold \(E^*\), and (3) the correlation \(\rho_{12}\). The correlation will not be zero if any of the components of \(\text{ERN}_0\) are significant. The additional parameter will be identified if there is at least one regressor affecting the participation decision but not affecting program assignment.\(^2\) That is, at least one of the coefficients in \(\zeta'_a\) must be zero, while the corresponding coefficient of \(\zeta'_p\) is not. The additional variable in the participation equation allows exogenous variation in that equation, conditional on the \text{X} variables appearing in the assignment equation. This is not an unreasonable requirement given that the participation decision is made by the worker and the program assignment is made by the program administrator.

\(^2\)This issue of identification of sequential probit models is discussed by Lillard and Danzon (1981).
Structural parameters may be estimated using the stage 1 instruments for the components of ERN₀. For these to be valid instruments, and for these parameters to be identified, there must be at least one variable affecting each component of ERN₀---i.e., in X₀---but not directly affecting the subprogram assignment decision. These structural probit equations provide estimates of ξ'ₐ and ξ'ₐ as well as the covariance terms Σ'ξ₀ua⁻¹.

Stage 4: Training Completion Equation Parameters

The parameters of the training completion equation are the same as those for the participation equation except that the variance is larger by σ² uc so that r₃₃ = r₄₁ + σ² uc. The variance ratio is k² = r₃₃/r₄₁ = (1 + σ² uc/r₄₁). The standardized coefficients (r₃) are equal to k times the standardized coefficients from the participation equation. The correlation between the reduced form residuals from participation and completion equations is k and the corresponding correlation between the program assignment and completion equations is k times the correlation between the participation and program assignment equations---i.e., k x r₂₁/(r₁₁ r₂₂). Therefore, only the parameter k must be estimated at this stage. This yields an estimate of the relative increase in the reduced form residual variance due to the introduction of new information attained after trainees enter the program.

The parameter k can be estimated without further restriction by a bivariate probit model using only information on participation and completion. Since all participants are assigned to some program, and program assignment is assumed not to affect completion,¹ the information on program type can be integrated-out without loss of information. The likelihood conditional on X is

\[
\text{Prob}(\text{TRN} = 1, \text{CMPL}|X) = \Phi[(x'ₚZ + x'ₚΓ₀X)/r₁, -k×(1 - 2 × \text{CMPL})] × (x'ₚZ + x'ₚΓ₀X)/r₁[-k×(1 - 2 × \text{CMPL})]
\]

where k is the only unknown.

¹This assumption can be relaxed, but a trivariate probit is required to estimate the correlation between the program assignment and job assignment equations.
Stage 5: Job Assignment Equation Parameters

The final training decision is whether the trainee is found a job to enter upon completion of training. The individual must have participated in training and must have completed training. In addition, he will have been assigned to one of the subprograms. The structural or reduced form parameters of the job assignment process can be estimated by a trivariate probit calculation.

The likelihood of participation, completion of training, and either assignment to a job or not is given by

\[
\text{Prob}(\text{TRN} = 1, \text{CMPL} - 1, \text{JOB}|\mathbf{X}) = \Phi\left((\gamma_p'\mathbf{Z} + \chi_p'\mathbf{G}_p\mathbf{X})/r_1, k \times (\gamma_p'\mathbf{Z} + \chi_p'\mathbf{G}_p\mathbf{X})/r_1, \right. \\
\left. - (1 - 2 \times \text{JOB}) \times (\gamma_j'\mathbf{Z} + \chi_j'\mathbf{G}_j\mathbf{X})/r_j, k, \\
- (1 - 2 \times \text{JOB}) \times r_4/(r_4 r_4), - (1 - 2 \times \text{JOB}) \times k \times r_4/(r_4 r_4)\right]
\]

where \(k\) is the correlation between the participation and completion equations, \(r_4/(r_4 r_4)\) is the correlation between the participation and job assignment equations, and \(k \times r_4/(r_4 r_4)\) is the correlation between the completion and job assignment equations.

First, consider the reduced form parameters. There are two additional parameters to be estimated, the regression value conditional on \(\mathbf{X}\) and the single reduced form correlation, because an estimate of \(k\) is already available. However, only one additional moment is available—the proportion of completers getting a job assignment. The correlation will not be zero if any of the components of ERN are significant or the structural residuals are correlated. Both parameters are identified if at least one variable affecting the participation decision does not affect the propensity to get a job assignment, so that there is exogenous variation in the participation regression conditional on the regressors in the job assignment equation. That is, there should be a zero restriction in \(\zeta_j'\) that is not in \(\zeta_p'\).
The additional reduced form correlation between job placement and program assignment, \( r_{42}'/(r_{42} r_{2}) \), can be estimated by the use of a quadrivariate probit with all levels of decision included. The correlation is identified if at least one variable affects program assignment, the earlier decision in the sequence, but not job assignment. That is, there is a zero restriction in \( \zeta_a' \) that is not in \( \zeta_j' \).

Structural parameters may be estimated using the stage 1 instruments for the components of ERN\(_0\). For these to be valid instruments, and for these parameters to be identified, at least one variable must affect each component of ERN\(_0\)--i.e., in \( X_0 \)--but not directly affect the job placement decision. These structural probit equations provide estimates of \( \zeta_j' \) and \( X_j' \) as well as the covariance terms \( \Sigma_{0uj} \).

### Stage 6: Structural Regression Equation

#### Parameters for WAGES, WEEKS, and HOURS

The standardized reduced form training decision equation parameters estimated in the stages above may be used to obtain estimates of the parameters of the earnings component equations including the effects of the endogenous training variables. Consistent estimates of parameters, but not standard errors, may be obtained by estimating Eqs. (2.1) through (2.3) using OLS on the pooled cross-section time-series data both before and after training, but including in the equation an instrument for the expected value of the residual conditional on the training variables PGM.

Here we specify the relationship to be estimated and the instruments in the form of the vector \( Y \) of all observations on all components as denoted earlier. The regression equation is

\[
Y' = \Lambda_j \Gamma_j X + \Lambda_j \xi
\]
\[ X' = [X', PGM', XT'_{01}, \ldots, XT'_{0T}, XT'_{11}, \ldots, XT'_{1T}] \]

The expected value of the residual \( A_y \xi \) conditional on PGM is

\[
E[A_y \xi | PGM] = A_y (R_{01} R_{02} R_{03} R_{04}) R_{5j}^{-1} E[\begin{bmatrix} u_p \\ u_a \\ u_p + u_c \\ u_j \end{bmatrix} + \begin{bmatrix} \chi'_p \\ \chi'_a \\ \chi'_p \\ \chi'_j \end{bmatrix}] \xi_0 | PGM]
\]

where the \( R_{5j} \) covariance matrices (column vectors) are the first four elements of the fifth row of \( R = B \Sigma B' \).

The expected values of the reduced form residuals of the training equations conditional on the training decisions represented by PGM can be computed based on the parameter values estimated in the earlier stages above. The outcomes represented in PGM are (1) TRN = 0; (2) TRN = 1, CLS = 1, and CMPL = 0; (3) TRN = 1, OJT = 1, and CMPL = 0; (4) TRN = 1, PSE = 1, and CMPL = 0; (5) TRN = 1, CLS = 1, CMPL = 1, and JOB = 0; (6) TRN = 1, OJT = 1, CMPL = 1, and JOB = 0; (7) TRN = 1, PSE = 1, CMPL = 1, and JOB = 0; (8) TRN = 1, CLS = 1, CMPL = 1, and JOB = 1; (9) TRN = 1, OJT = 1, CMPL = 1, and JOB = 1; and (10) TRN = 1, PSE = 1, CMPL = 1, and JOB = 1. Each of these represents a subspace of the reduced form residual domain as noted above. For example, the expected value for (1) is given by the expectation of the reduced form participation equation residual conditional on it being negative; i.e.,

\[
E(u_p + \chi'_p \xi_0 | TRN = 0) = E(nv | nv \leq -(\gamma'_p Z + \chi'_p \Gamma_0 X) | r_{11})
\]
where \( nv \) is a normal variate with mean 0 and variance \( r_{11} \). The other residuals are unconstrained and thus have zero mean. The expected value given (2), (3) or (4) involves three of the residuals and the remainder involves four. The expected values conditional on (2) are

\[
E(\text{up} + \chi_p\xi_0 \mid \text{TRN} = 1, \text{CLS} = 1, \text{CMPL} = 0) =
E(nv_1 \mid nv_1 > -\langle \tau_p'Z + \chi_p'\Gamma_0X \rangle, nv_2 \leq -\langle \tau_p'Z + \chi_p'\Gamma_0X \rangle, nv_3 \leq \tau_p'Z + \chi_p'\Gamma_0X | \]
\[ r_{11}, r_{21}, r_{22}, r_{31}, r_{32}, r_{33} \}
\]

\[
E(\text{ua} + \chi_a\xi_0 \mid \text{TRN} = 1, \text{CLS} = 1, \text{CMPL} = 0) =
E(nv_2 \mid nv_1 > -\langle \tau_p'Z + \chi_p'\Gamma_0X \rangle, nv_2 \leq -\langle \tau_p'Z + \chi_p'\Gamma_0X \rangle, nv_3 \leq \tau_p'Z + \chi_p'\Gamma_0X | \]
\[ r_{11}, r_{21}, r_{22}, r_{31}, r_{32}, r_{33} \}
\]

\[
E(\text{uc} + \chi_p\xi_0 \mid \text{TRN} = 1, \text{CLS} = 1, \text{CMPL} = 0) =
E(nv_3 \mid nv_1 > -\langle \tau_p'Z + \chi_p'\Gamma_0X \rangle, nv_2 \leq -\langle \tau_p'Z + \chi_p'\Gamma_0X \rangle, nv_3 \leq \tau_p'Z + \chi_p'\Gamma_0X | \]
\[ r_{11}, r_{21}, r_{22}, r_{31}, r_{32}, r_{33} \}
\]

Similar expectations can be derived for the other cases. This procedure also provides estimates of the reduced form covariance terms in the \( R_{5j} \).

**FULL INFORMATION MAXIMUM LIKELIHOOD (FIML) PARAMETER ESTIMATION**

Rather than specify the FIML function over the full sample, we present the observation level likelihoods for each of the four types of observations: (1) nonparticipants, (2) participants not completing the training program, (3) participants completing the training program but not placed in a job, and (4) participants who are placed in jobs upon completion of the program. We discuss issues of identification of parameters at the points in the presentation where the result should be most clear.
Branch 1: Nonparticipants

For those who choose not to participate in the training program, TRN = 0, we know from Eqs. (3.1) and (3.2) that

\[ Ap \leq 0 \rightarrow up \leq -(\gamma'_p Z + \chi'_p \text{ERN}_0) \]

where \( \text{ERN}_0 \) is the value of ERN for pre-training values only, \( \text{ERN}_0 = \Gamma'_0 X + \xi'_0 \). In reduced form the relationship becomes

\[ up + \chi'_p \xi'_0 \leq -(\gamma'_p Z + \chi'_p \Gamma'_0 X) \]

The vector of regressors \( Z \) includes variables reflecting the cost of training and its benefits. Pre-training earnings components appear in \( \text{ERN}_0 \). Identification of parameters requires that certain variables affecting these pre-training earning components (in \( X \)) do not directly affect the participation decision (in \( Z \)).

The likelihood of nonparticipation conditional on the observable variables is given by

\[ \int_{-\infty}^{0} f(A_p, Y) \, dA_p \]

or alternatively in terms of the observables and normal variates

\[ -(\gamma'_p Z + \chi'_p \Gamma'_0 X) \int_{-\infty}^{0} n[v_p, C|M_1] \, dv_p \]
where \( n \) indicates the \( k \)-variate normal density function of appropriate dimension with zero mean. The \( C' \) arguments are the observed residuals related to the wage, weeks, and hours equations:

\[
C = (Y - \Lambda_y \Gamma_s X - \Lambda_y \Gamma_p \text{PGM})
\]

The covariance matrix \( M1 \) is obtained by taking the appropriate rows and columns of \( B \Sigma B' \).

**Branch 2: Participants Not Completing Training**

For those who begin a training program but drop out before completing it, the program assignment is also known. From the participation condition given in Eqs. (3.1) and (3.2) and the program assignment conditions given in Eqs. (3.3) to (3.6) we know that

\[
\begin{align*}
Ap > 0 \rightarrow u_p + \chi'_p \xi_0 &> -(\xi'_p Z + \chi'_p \Gamma_0 X) & \text{participate TRN} = 1 \\
E \leq 0 \rightarrow u_a + \chi'_a \xi_0 &\leq -(\xi'_a Z + \chi'_a \Gamma_0 X) & \text{CLS} = 1 \\
0 < E \leq E^* \rightarrow -(\xi'_a Z + \chi'_a \Gamma_0 X) \leq u_a + \chi'_a \xi_0 \leq E^* - (\xi'_a Z + \chi'_a \Gamma_0 X) & \text{OJT} = 1 \\
E^* < E \rightarrow E^* - (\xi'_a Z + \chi'_a \Gamma_0 X) < u_a + \chi'_a \xi_0 & \text{PSE} = 1 \\
\text{and } Ac = 0 \rightarrow u_c + u_p + \chi'_p \xi_0 \leq -(\xi'_p Z + \chi'_p \Gamma_0 X) & \text{drop out CMPL} = 0
\end{align*}
\]

Pre-training earnings components appear in the equations for program choice and for completion. Identification of parameters requires variables affecting these pre-training earnings components (in \( X \)) that do not directly affect the assignment to program. If the stochastic part of program assignment, \( u_a \), is not assumed independent of the stochastic part of participation, \( u_p (\sigma_{up} = 1) \), then some regressor
variable must affect participation but not program assignment. Because participation decisions are made primarily by workers based on costs and benefits, and local prime sponsors decide on program assignment, such a restriction is reasonable. The innovation in the stochastic participation equation is that \( \sigma_{uc} = 1 \), which determines completion, is assumed independent of all other stochastic elements and thus causes no identification problem.

The likelihood for observations dropping out of training from the three program types is given by

\[
\int_{0}^{\infty} \int_{-\infty}^{0} \int_{-\infty}^{0} f(A_p, A_c, E, Y) \, dE \, dA_c \, dA_p \text{ for CLS}
\]

\[
\int_{0}^{\infty} \int_{-\infty}^{0} \int_{0}^{E'} f(A_p, A_c, E, Y) \, dE \, dA_c \, dA_p \text{ for OJT}
\]

\[
\int_{0}^{\infty} \int_{-\infty}^{0} \int_{0}^{E'} f(A_p, A_c, E, Y) \, dE \, dA_c \, dA_p \text{ for PSE}
\]

An illustrative example of the more detailed likelihood value is given for the case of OJT.

\[
\int_{0}^{\infty} \int_{-\infty}^{0} \int_{-\infty}^{0} d\nu \, d\mu \, d\sigma \, d\theta
\]

The covariance matrix \( M2 \) is obtained by taking the appropriate rows and columns of \( B \Sigma B' \).
Branches 3 and 4: Participants Completing the Training Placed in a Job or Not

Some of those who complete a training program are placed in a job while others are not. The estimation procedure is the same as that just discussed except that the completion condition is satisfied

\[ Ac > 0 \Rightarrow uc + up + x_{p}\xi_0 > -(x'_p Z + x'_p \Gamma_0 X_0) \text{ complete} \]

and another decision, placement or not, is encountered.

\[ Aj > 0 \Rightarrow w_j + x'_j \xi_0 > -(x'_j Z + x'_j \Gamma_0 X) \text{ placed in a job} \]

\[ Aj \leq 0 \Rightarrow w_j + x'_j \xi_0 \leq -(x'_j Z + x'_j \Gamma_0 X) \text{ not placed in a job} \]

Again for identification we need variables affecting pre-training earnings but not directly affecting placement, and we need at least one variable affecting each earlier decision but not placement.

The likelihood of job placement for observations completing on-the-job training is given by

\[
\int \int \int \int f(A_p, A_c, E, A_j, Y) \, dA_j \, dA_c \, dE \, dA_p
\]

and of no job placement is

\[
\int \int \int \int f(A_p, A_c, E, A_j, Y) \, dA_j \, dA_c \, dE \, dA_p
\]
IV. CONCLUSION

The extensive literature on methodological issues related to the evaluation of CETA-like manpower training programs has concentrated on the estimation of the effect of participation in the program on the earnings of participants. Emphasis was on the endogeneity of training, on the use of longitudinal earnings data, and on the potential effects of temporarily low earnings just before the training period. Several alternative estimation methods have been proposed based on this basic setup. However, empirical evaluation research has directed attention to the various types of training programs within CETA and on the source of the effects of training on earnings. Substantial differences have been noted.

In this Note we bring together various aspects of training and its effects and provide an econometric methodology for the evaluation of these programs. It introduces more detail about the actual programs and more detail about earnings.

Concentration on the broad concept of earnings masks the potentially rich information on the components of and changes in earnings. We decompose annual earnings into the hourly wage rate, weeks worked, and hours per week. Within these earnings components we decompose each into the more usual, individual, and time varying components. An implication of this decomposition is that it is possible to find out the source of low income that leads to participation in a training program—e.g., low wage versus few weeks worked and low hours per week—and it is possible to estimate the source of enhanced earnings in similar terms. In addition, the model explicitly treats the issue of the timing of the training effect after completion of training.

An important feature of the Note is the explicit introduction of important dimensions of the training experience into the analysis. It recognizes the difference between participation and completion of a training program and that the two are interrelated. It characterizes the various subprograms within CETA, classroom training, on-the-job training, and public service employment. Assignment to these different
subprograms is surely not random. Similarly, placement in a job upon completion of the training program is endogenous and provides a direct advantage to some.

Failure to specify the earnings and training program variables, and failure to incorporate the endogeneity of the training sequence will lead to confounding of effects and unstable estimated program effects. Studies considering only earnings and participation in or completion of a training program may be expected to be fairly unstable across studies and periods of time because of differences in the composition of the training experiences of the groups of trainees and the differences in the various sources of effects on earnings.

The formulation of the model is very general, incorporating many special cases, and can be adapted to different program types. However, the model is naive in its assumptions including the availability of ideal data and multivariate normality.
BIBLIOGRAPHY


