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CORRECTION OF ESTIMATION BIAS IN EVALUATING THE LABOR MARKET OUTCOMES OF YOUTH PARTICIPATING IN SCHOOL-BASED LEARNING PROGRAMS IN THE UNITED STATES

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ABSTRACT

Evaluations of training programs, among others, have struggled with the prevention of estimation bias, especially when examining programs using non-experimental data. Alternative econometric approaches have been developed to correct for this estimation bias. This bias is mostly due to discrepancies in observed and unobserved characteristics between the participants and the counterfactual. The purpose of this study is to explore the unbiased estimates derived from alternative corrections and compare variation in predictive effectiveness among different corrections from evaluations of school-based learning (SBL) programs.

This study uses data from the National Longitudinal Survey of Youth 97 (NLSY 97), a non-experimental database, to evaluate the effects of U.S. youths' school-based learning (SBL) program participation on early labor market outcomes. Estimates from ordinary least squares regression, the linear regression with probabilistic matching or instrumental proxy, are compared to those obtained from bootstrapping regression analysis. Four outcome variables, including employment in college, employment, total worked hours and hourly wage rate, are used to gauge the early labor market outcomes of youth from the NLSY 97.

Findings, at an alpha level of .05 when the first type of instrumental variable (IV) correction method is adopted, reveal that SBL program participants are significantly less likely than non-participants to enroll in college, and that SBL program participants have a lower probability of enrolling in college than do non-participants.

In comparison with college enrollment, findings from the analysis of employment

and total worked hours outcomes on SBL program participation are not statistically significant with selection bias corrections. Rather, only the estimates derived from the Tobit regression for the correction of the censored data show that SBL program participants have a lower number of total worked hours than do non-participants. Due to evidence which shows that youths' wage differential is small in the early labor market, the findings from Heckman's two-step correction with an alpha level of .10 show that SBL program participants are more likely to have higher hourly wages than non-participants.

In addition, in looking at the seven specific types of SBL program participation, the significant likelihood of enrolling in college or being employed, all of the estimates derived from Heckman's two-step correction show no significance.

For the total worked hours outcome, the correction of the censored data using the Tobit regression shows that internship/apprenticeship program participants have lower total worked hours than non-participants, with an alpha level of .001.

Due to the small wage rate differential for youth in the early labor market, a significance level of .10 is used for this outcome. Heckman's two-step correction reveals that SBL program participants are more likely than non-participants to have higher hourly wage rates. In view of the seven types of SBL program participation, the findings from Heckman's correction reveal that internship or apprenticeship program participants are more likely than non-participants for all SBL programs to have a higher hourly wage rate.

In summary, this study shares corrected estimates from alternative approaches. Based on criteria from the 200-time and 500-time bootstrapping, the best selection bias estimation among these four corrections uses Heckman's two-step correction.

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Chapter 1

Introduction

Background of the Study

Since the 1990s, increasing attention has been paid to youth training programs and their influences upon trainees in the labor market (Lynch, 1992, 1993; Rothstein, 2001a, 2001b). To improve the school-to-work systems for the youth population, the 1994 School-to-Work Opportunities Act (STWOA) provided state and local partnerships with federally funded grants that totaled approximately $1.5 billion from fiscal 1995 to 1998. The STWOA was developed to promote school-based learning (SBL), work-based learning (WBL), and their connecting activities. Its goal was to help the U.S. youth population make decisions about post-high-school careers and improve their transitions from school to work (Neumark & Rothstein, 2003).

Evaluations of school-to-work (STW) transition programs with respect to variations in and consequences of participation reveal common findings. For example, females are more likely than males to participate in any type of STW transition programs (Hershey, Silverberg, & Haimson, 1999; Joyce & Neumark, 2000; Passmore, Chen, Okou, Yu, & Lin, 2003; Yu & Passmore, 2004). African American students are also more involved than those from other ethnic groups in STW transition programs (Ibid.).

No consensus has yet been reached about the evaluation of the consequences of participation in STW transition programs. A great deal of research has suggested that youth participation in STW transition programs was associated with the labor market outcomes of their participation (Bishop, Mane, & Ruiz, 2001; Lewis, Gardner, & Seitz, 1983; Stern, Finkelstein, Stone, Latting, & Dornsife, 1994). Other researchers have pointed to the weak relationship between program participation in STW and its subsequent school outcomes. Hershey et al. (1999) indicated that participation in STW transition programs could help the youth population to clarify career goals 18 months after graduation. Neumark and Rothstein (2003) also argued that only one STW transition program, school-sponsored enterprises, was positively related to the subsequent educational decisions of the youth population. Other types of STW transition programs, such as cooperative education and internships/apprenticeships, were positively associated with subsequent youth employment. Unlike Neumark and Rothstein's findings (2001, 2003), Yu and Passmore (2004) used NLSY97 data sets to examine the relationship between SBL participation and its outcomes. They found that participants in both career major and internships/apprenticeships are more likely to be employed than non-participants.

Nonetheless, the evaluation of the consequences of participation in STW transition programs is not an easy task. Regression analysis using non-experimental data needs to be adjusted to allow for biased estimations (Barnow, 1987; Friedlander, Greenberg, & Robins, 1997; Heckman, Ichimura, & Todd, 1997). For example, in making a finite sample estimation to estimate a single parameter in the above evaluation, the implication is that an estimator of a parameter θ is biased:

$$\mathrm{E}(\hat{\theta}) \neq \theta ,$$

or

$$E(\hat{\theta}-\theta) = \text{Bias}(\hat{\theta} \mid \theta) \neq 0 .$$

Thus, if the unbiased parameter θ had to be estimated in the process of evaluating in training programs, the parameter's expected sampling error would be zero (Greene, 2000). Let us consider the following example, which evaluates how participation in the STW transition programs affects individuals' wages. Suppose that the training outcomes and participation decision may be simply described as follows:

$$Y_{it} = c_t X_i + b_t P_{i0} + \mu_{it} \ , \ t > 0 , \tag{1}$$

$$P_{i0} = a_0 Z_i + \nu_{i0} , \tag{2}$$

where Y_{it} is the ith individuals' wages in period t and $t = 0$ represents the period of the training. μ_{it} is the unobserved characteristics in Equation 1. X_i and Z_i (perhaps overlapping) represent exogenous factors and individual characteristics that are measured before participation. P_{i0} is a binary variable that depends on both observed characteristics Z_i and unobserved characteristics ν_{i0} with value one indicating participation. In this model, the estimates of b_t are the mean effect of training participation. Then the evaluation procedure is practically based on a comparison of the wage measures of participants and non-participants. If experimental data are available, the comparison group, which is called a control group, consists of individuals who are randomly assigned to participation. In contrast with a non-experimental evaluation, the comparison group consists of individuals assumed to be comparable to participants but who have not participated in the program. The focus of the major issue in the non-experimental evaluation is the construction of an ideal counterfactual that is comparable to that for participants (Friedlander, Greenberg, & Robins, 1997; Manski & Garfinkel, 1992; Moffitt, 1991).

The counterfactual is a logical condition that assumes a possible condition in which the program participants had not participated. The characteristics of the participants observed in this counterfactual are otherwise similar to the original characteristics of the program participants and are described through a model that estimates observed outcome variables—i.e., participants' wages. However, an inconsistency may be found in the observed and unobserved characteristics between the participants and their counterfactual in practice. Failure to control those characteristics through the use of statistical-adjustment techniques means that the comparison between participants and the counterfactual cannot afford unbiased results in a non-experimental evaluation. For Equation 1, the unbiased estimate of b_t cannot be obtained by regressing Y_{it} on X_i and P_{i0}, if P_{i0} is correlated with μ_{it}. That is, if $\mathrm{E}(P_{i0}u_{it}) \neq 0$, $E(\widehat{b_t}) \neq b_t$. This estimation bias is the so-called selection bias (Heckman, 1979). This bias could occur in practice. For example, individuals with lower post-high-school expectations may be more likely to opt to participate in training, but their post-high-school expectations may not be captured in variables X_i; this omission is due to the selection bias in observables or unobservables in Equation 2. This means the correlation arises through Z_i or through ν_{i0}. If $\mathrm{E}(\mathrm{Z_i}u_{it}) \neq 0$, but $\mathrm{E}(u_{it}\nu_{it}) = 0$, the correlation arises from selection on observables. This would occur in practice, for example, when program administrators select applicants by some criteria based on a set of known characteristics. For instance, individuals might be chosen to attend this program because of their poor levels of school achievement (Heckman & Robb, 1985; Heckman & Hotz, 1989). Inclusion of the selection variables Z_i as the regressors resolves this selection-bias problem (Barnow, Cain, & Goldberger, 1980).

By contrast, if $\mathrm{E}(\mathrm{Z_i} u_{it}) = 0$, but $\mathrm{E}(u_{it} v_{it}) \neq 0$, the selection depends on unobservables. This selection-bias problem may occur when individuals are prompted to participate in the program due to some unobserved characteristics such as motivation or expectations for their future employment status. The selection bias on unobservables is more serious than that resulting from observables. More complex correction procedures such as Ashenfelter's (1978) fixed-effect model and Heckman's (1997) random-coefficient model are used to solve the estimation bias.

Statement of the Problem

Since the 1970s there has been a consensus among policy makers about the importance and necessity of evaluating training programs. However, for the selection-bias problem mentioned above, unbiased estimates cannot be obtained for the non-experimental evaluation if researchers fail to adjust for the estimation procedure. The evaluation problem is due to the discrepancies in observed and unobserved characteristics between the participants and the counterfactual. Let us consider two equations with a more general version of potential outcome functions than are found in Equations 1 and 2:

$$Y^1 = \mathrm{g}^1(X) + U^1, \qquad (3)$$

$$Y^0 = g^0(X) + U^0, \tag{4}$$

in which the outcome variables, (Y^0, Y^1), are associated with the superscript, the training state "1" or the no-training state "0", and they are assumed to depend on both observed X and unobserved U characteristics. The functions g^i stand for the relationship between the potential outcomes and the observable characteristics. The error terms (U^0, U^1) with mean zero are assumed to be uncorrelated with X. The other assumption is that the observed characteristics X are not affected by the training treatment.

The participation decision may be described as the decision equation:

$IN = f(Z) + V$,

$D = 1$ if $IN > 0$,

$D = 0$ otherwise,

IN represents an index that depends on both observed Z and unobserved V characteristics. D is a dummy variable that represents the enrollment status in the training program. The original treatment effect for characteristics X may be described as:

$$\alpha(X) = Y^1 - Y^0 = [g^1(X) - g^0(X)] + (U^1 - U^0).$$

In general, the response to the training programs for individual participants may not be exactly the same. As a result, evaluation methods are needed to deal with the heterogeneity across individuals. Under the assumption of homogeneous treatment effects, the above measures are identical but the treatment effect will vary across individuals. Consequently, the difference between the outcome equations under the consideration of heterogeneity will show different individual-specific treatment effects

(Avkvik, Heckman, & Vytlacil, 2005; Blundell & Costa Dias, 2002). Therefore, Equation 3 may be re-written as:

$$Y = DY^1 + (1-D)Y^0 = g^0(X) + \alpha(X)D + U^0$$

$$= g^0(X) + \alpha(X)D + [U^0 + D(U^1 - U^0)]\text{, such that}$$

$$\alpha(X) = \mathrm{E}[\alpha(X)] = g^1(X) - g^0(X)\,,$$

where $\alpha(X)$ is the expected treatment effect that is captured by characteristics X .

To assess this average effect, the methods may address these major evaluation parameters of interest: the population average treatment effect (ATE), which shows the outcome if the treatment is randomly assigned across individuals, the average treatment effect on the treated (TTE), and the effects on the untreated (TU). The effects may be described as follows:

Average Treatment Effect (ATE):

$$\alpha_{\mathrm{ATE}} = \mathrm{E}(\alpha \mid X = x) = \mathrm{E}(Y^1 - Y^0 \mid X = x) = \mathrm{ATE}(X)$$

Average Treatment on the Treated Effect (TTE):

$$\alpha_{\mathrm{TTE}} = \mathrm{E}(\alpha \mid X, \mathrm{D} = 1) = \mathrm{E}(Y^1 - Y^0 \mid X = x, D = 1) = \mathrm{TTE}(X)\,,$$

Average Treatment on the Untreated Effect (TU):

$$\alpha_{\mathrm{TU}} = \mathrm{E}(\alpha \mid X = x, D = 0) = \mathrm{E}(Y^1 - Y^0 \mid X = x, D = 0) = \mathrm{TU}(X)\,.$$

With information from Equations 3 and 4, researchers may evaluate in practice the effects on average wages. The most commonly asked question about the evaluation methods concerns the average program's effect on individuals.

A counterfactual, $\mathrm{E}(Y^0 \mid X = x, D = 0)$, is used to proxy the participants if they had not participated in the program. Comparing the average wages of the two groups (Heckman, 2001):

$$\mathrm{E}(Y^1 \mid X = x, D = 1) - \mathrm{E}(Y^0 \mid X = x, D = 0) =$$

$$\underbrace{\mathrm{E}(Y^1 - Y^0 \mid X = x, D = 1)}_{\mathrm{TTE}(X)} + \underbrace{\mathrm{E}(Y^0 \mid X = x, D = 1) - \mathrm{E}(Y^0 \mid X = x, D = 0)}_{\text{Selection bias}} .$$

In this comparison, if $\mathrm{E}(U \mid D, X) \neq 0$, then:

$$\mathrm{E}(\hat{\alpha}_{\mathrm{ATE}}) = \alpha + \underbrace{[\mathrm{E}(U \mid D = 1) - \mathrm{E}(U \mid D = 0)]}_{\neq 0},$$

This means that selection problems from either the observables or the unobservables occur, and selection bias arises. Econometric approaches need to consider the problem of controlling the characteristics affecting outcome variables and the participation decision simultaneously.

If the experimental data are available, the social experiment method may be the most convincing method of program evaluation. Because the method is designed to use experimental data based on participants randomly assigned from the eligible population, it may solve the missing data problem (Bassi, 1983, 1984; Cochrane & Rubin, 1973; Fisher, 1951). However, social experiments are so expensive to implement that the experimental data usually are unavailable. Four major approaches help solve the problem of assessing training effects: difference-in-differences method, Heckman's two-step correction, instrumental variable method, and matching method. These approaches construct the counterfactual that is used in program evaluation in empirical microeconomics (Blundell & Costa Dias, 2002; Heckman, LaLonde, & Smith, 1999).

The following three approaches may use non-experimental data to mimic randomized control and to estimate effects rather than depending on experimental data. The natural experiment method attempts to construct a comparison group that simulates a properly designed experiment. The treatment effect is estimated by comparing the differences between outcome measures before and after program participation. This is known as the so-called difference-in-differences method (Ashefelter & Card, 1985; Eissa & Liebman, 1996). Heckman's two-step correction uses an explicit model with a control for the participation decision. In the matching method, researchers eliminate the systematic differences between two individuals' reactions towards program participation; they select sufficient observable factors similar to those treated for a comparison group. Consequently, the training effects may be measured through this matching (Heckman et al, 1997, Heckman, Ichimura, & Todd, 1998; Rosenbaum & Rubin, 1985; Rubin, 1979). The instrumental variable (IV) method adopts an econometric approach to solving the endogeneity problem. This means that some specific explanatory variable may be a choice variable in correlation with unobservable factors that may be related to the error term in the regression model. In other words, this specific independent variable may be endogenous if it is associated with unobservable factors that affect outcomes. The IV method selects a variable excluded from the outcome equation but that is also a determinant of program participation. The IV estimators can identify the treatment effect from which have been removed all biases that emanate from a non-randomized control in the simple linear model (Heckman, & Vytlacil, 1998; Imbens & Angrist, 1994).

The focus of this study is the use of different estimation methods such as matching techniques, and IV methods to overcome the evaluation problems resulting from selection bias using non-experimental data, and the comparison of different estimates among alternative estimators. However, the absence of large representative non-experimental data sets with information on STW transition programs also has been a critical problem for researchers in the past. The Bureau of Labor Statistics (BLS), U.S. Department of Labor, has initiated a new program known as the National Longitudinal Survey of Youth 1997(NLSY 97). In contrast with the old database, titled NLSY 79, the new NLSY 97 provides researchers with direct evidence to analyze the consequences of participating in school-based learning programs. In the NLSY 97, respondents were asked to respond to a set of survey questions about programs and schools that help students prepare for the world of work, and if they had ever participated in any of these programs through their schools. According to the Center for Human Resource Research (2002), the seven school-based learning programs are as follows:

Career major-- A coherent sequence of courses based upon an occupational goal.

Cooperative education-- Students alternate or parallel their academic and vocational studies with a job in a related field.

Internship or apprenticeship-- Students work for an employer for a short time to learn about a particular industry or occupation.

Job shadowing-- A student follows an employee for one or more days to learn about an occupation or industry.

Mentoring-- A student is paired with an employee who assesses his or her performance over a period of time, during which the employee helps the student master certain skills and knowledge.

School-sponsored enterprise-- The production of goods or services by students for a sale or use by others. Enterprises typically involve students in the management of a project.

Tech prep-- A planned program of study with a defined career focus that links secondary and postsecondary education (p. 88).

Purpose of the Study

The purpose of the present study is to explore the comparative estimates derived from alternative estimation methods when the methods are used to evaluate the subsequent outcomes after participation in SBL programs. This study uses individual-based observations from the NLSY97, a non-experimental database, to analyze the effectiveness of school-based learning programs and individual decision-making behavior. This study is methodological in comparing alternative approaches to correcting estimation bias. Estimates from ordinary least squares regression, the linear regression with Heckman's two-step correction, probabilistic matching, and instrumental proxy, are compared to those obtained from bootstrapping regression analysis.

Research Questions

The research questions that guide this study are as follows:

1. Do college enrollment outcomes vary among youth from the NLSY 97 by school-based learning (SBL) program participation?
2. Do employment outcomes vary among youth from the NLSY 97

by school-based learning (SBL) program participation?

3. What is the mean effect of school-based learning (SBL) program participation as measured by the total worked hours by youth from the NLSY 97?
4. What is the mean effect of school-based learning (SBL) program participation as measured by the hourly wage rate for youth from the NLSY 97?
5. Do college enrollment outcomes vary among youth from the NLSY 97 by the seven specific types of school-based learning (SBL) program participation?
6. Do employment outcomes vary among youth from the NLSY 97 by the seven specific types of school-based learning (SBL) program participation?
7. What is the mean effect of the seven specific types of school-based learning (SBL) program participation as measured by the total worked hours by youth from the NLSY 97?
8. What is the mean effect of the seven specific types of school-based learning (SBL) program participation as measured by the hourly wage rate for youth from the NLSY 97?

The remainder of this thesis is organized as four chapters. Chapter 2 provides a review of the related literature about theories and empirical studies. Chapter 3 consists of sample construction, target population and sample, dependent variables, independent variables, and analysis methods. Finds from this study are reported in chapter 4. Chapter 5 presents the summary, discussions and recommendations from the study.

Chapter 2

Literature Review

This study reports the results from an exploration of the consequences of school-to-work transition programs and comparison outcomes from the use of alternative estimation methods. To provide the context for this study, this chapter reviews relevant literature on the alternative approaches to evaluating training programs with non-experimental data. It consists of three parts: the evaluation problem, solutions using different econometric estimators, and empirical studies about the argument over the non-experimental estimators.

The Evaluation Problem

The literature on the problem of evaluating training programs focuses primarily on measuring the effectiveness of program interventions on individuals. The outcome variables may include individual employment status and earnings. Individuals may be identified in the evaluation using observable characteristics. Consequently, the basic evaluation problem defines an ideal comparison group and measures the training effects on these identified individuals (Blundell & Costa Dias, 2000). The same individuals in the treated and untreated states may then be compared. This strategy is widely used as the so-called before-after estimation. An alternative option is to choose the comparison group using different persons from the internal or external samples (Heckman et al., 1999).

However, it is difficult to observe the outcome variable for program participants if they have not participated. The methodological challenge as reported in the literature on evaluating training programs is in constructing counterfactuals. In addition, if participants self-select or are not randomly assigned to participation by researchers, the problem of selection bias arises. This is the sample selection problem discussed earlier.

The literature on this sample selection problem notes major changes in program evaluation (Gronau, 1974; Heckman, 1974, 1979). Sample survey methods and the individual's self-selection decisions or both can cause bias in the selection procedure (Heckman, 1985). Ashenfelter and Card (1985) and Heckman and Robb (1985, 1986) pointed out many econometric methods for solving the evaluation problem, and emphasized focusing on the labor market area. This resolution arises from the non-random assignment of participants into training programs.

When the experimental data are available, the counterfactuals may be obtained to correct the evaluation problem resulting from the selection bias. The random assignment of program participants may eliminate bias from individual self-selection. The randomly assigned participants are independent from the outcome variable or the program effect (Blundell & Costa Dias, 2002). In contrast, the studies using non-experimental data have to face the evaluation problem that arises from missing data. An individual only can be observed either in the program or not, but not simultaneously—the so-called missing problem. To correct this estimation problem, a design is needed that includes sampling strategies and alternative econometric estimators that eliminate observational problems.

The Solutions Using Alternative Econometric Estimators

Heckman et al. (1997) note that several factors can help non-experimental methods to amend the misrepresentation of the true population: the similarity of the unobservable and observable characteristics of the treated and the untreated, the same selection rules for the treatment and comparison groups, and a similar local labor market for participants and comparison groups. To fit in these factors, an alternative econometric method may be used. The trade-off limitation stems from the availability of longitudinal or repeated cross-section data and the program parameters of interest.

The literature on different econometric estimators for the correction of the evaluation problem is vast. The development of the analysis for correcting the evaluation problem has four major estimators. If repeated cross-section data can be obtained, only two estimators can be used in the non-experimental analysis: the instrumental variables (IV) and the two-step Heckman selection estimators. If longitudinal data are available or the cross-section data are not single-format, the difference-in-differences estimators may be applied to estimate program effects under the requirement of an additive specification of the error term. If either longitudinal or cross-section data are available, then an alternative choice is the matching estimator. However, the reliability and robustness of the matching estimator relies on abundant individual information from the treated and untreated (Blundell & Costa Dias, 2000).

The Two-Step Heckman Selection Estimators

According to Heckman (1979), the basic design process of this estimator adds at least one regressor to the behavior decision rule equation. This additional regressor needs to have a non-zero estimate in the decision rule equation, and it is not related to the error term in the outcome equation. In addition, the joint density of the distribution of the error term for the outcome and decision rule equation needs to be estimated simultaneously. By controlling the error term in the outcome equation, the two-step regression can obtain more robust estimates. The first step is to estimate the part of the error term in the original outcome equation that is related to the dummy variable that decides training participation. These estimates are then used in the outcome equation and regression, and the outcome equation is again regressed.

The Matching Estimators

When using non-experimental data to evaluate training programs, the matching method is the most commonly used. The major aim of the matching method is to stimulate conditions when experimental data are not available. It uses observed explanatory variables to construct a sample counterpart to adjust the missing information that results in selection bias. By pairing individuals with the untreated comparison group, the differences in outcome variables unrelated to treatment may be eliminated (Blundell & Costa Dias, 2002; Heckman et al., 1999). The assumptions of the matching method advocated by Rosenbaum and Rubin (1983, 1985) are:

$\text{A1}: (Y^1, Y^0) \perp D \mid X$,

and

$\text{A2}: 0 < \Pr(D = 1 \mid X) < 1$,

where " $\perp$ "denotes "independent." The first assumption is that the outcome variables are independent of participation status, which is represented by the dummy variable D, given the conditional on the set of observable characteristics X. If assumption A1 is valid, the non-participants may be used as the required counterfactual for measuring the outcome, had these individuals not participated given variables X. The second assumption ensures the existence of this counterfactual. Under both assumptions, the matching method constructs a comparison group that re-builds the experimental conditions, and the distribution of the counterfactual outcome for the participants is equal to the distribution for the comparison group. In particular, assumption A2 cannot guarantee that the counterfactual exists within any sample, especially for the specific training programs connecting special groups. According to Heckman et al. (1997) and Heckman et al. (1999), the matching method may also be used to estimate $\mathrm{E}(Y^1 - Y^0 \mid X, D = 1)$. Over a set of $\mathrm{S}(X)$, which represents the common support of X, a consistent estimator for TTE given assumption A1 and A2 may be conducted by $\mathrm{M}(S)$,

$$\mathrm{M(S)} = \frac{\int_{\mathrm{S}(X)} \mathrm{E}(Y^1 - Y^0 \mid X, D = 1) d\, \mathrm{F}(X \mid D = 1)}{\int_{\mathrm{S}(X)} d\, \mathrm{F}(X \mid D = 1)} \quad \text{At a time t > k,}$$

where program participation occurs at time k and t identifies the time period. Based on the measurement of TTE, which needs to be integrated over the measurement of $\mathrm{S}(X)$, the matching method faces a trade-off drawback. It needs to find the correct set of observable characteristics X such that the observations of non-participants have the counterfactual observations given the above two assumptions. However, the more detailed information causes more difficulties in constructing a similar comparison and tightly restricts common support of X.

Due to the limitation in measuring program dimensionality using a non-parametric method, the statistical literature adopts an alternative matching focus on a function of X. Most commonly, the use of the propensity score, $\mathrm{P}(X) = \Pr(D = 1 \mid X)$, which is advocated by Rosenbaum and Rubin (1983, 1984), is most feasible and simple. If assumptions A1 and A2 hold, then:

A3: $(Y^1, Y^0) \perp D \mid \mathrm{P}(x) \ \forall\ X \in X_c$,

where X_c is some specific set given the assumption A2. Assumption A3 implies that the counterfactual conditional mean $\mathrm{E}(Y^0 \mid \mathrm{P}(X), D = 1)$ may be obtained if $\mathrm{B}(\mathrm{P}(X)) = \mathrm{E}(Y^0 \mid \mathrm{P}(X), D = 1) - \mathrm{E}(Y^0 \mid \mathrm{P}(X), D = 0) = 0$. The original assumption in Rosenbaum and Robin’s study is that $\mathrm{P}(X)$ is supposed to be known rather than estimated. In more practical terms, Heckman, Ichimura, and Todd (1988) advocate the asymptotic distribution theory for matching when $\mathrm{P}(X)$ is either known or estimated.

The Difference-in-Differences (DID) Estimators

The basic design of the difference-in-differences estimators (Ashenfelter, 1978; Ashenfelter & Card, 1985) is to trace the treatment effect from measuring the outcome variable between the treated and the untreated. The DID estimators are described as:

$$\alpha_{\mathrm{DID}} = (\overline{Y}^{\mathrm{T}}_{\mathrm{t}_1} - \overline{Y}^{\mathrm{T}}_{\mathrm{t}_0}) - (\overline{Y}^{\mathrm{C}}_{\mathrm{t}_1} - \overline{Y}^{\mathrm{C}}_{\mathrm{t}_0}),$$

where $\overline{Y}^T$ and $\overline{Y}^C$ are the average treatment effects for the treated and untreated, respectively. This approach keeps any variables that correlated with the participation decision the same over time and this logic can reduce the selection bias for the outcome variables. However, this approach needs repeated observations from either panel data or repeated cross-sections data (Blundell & Costa Dias, 2000).

The Instrumental Variable (IV) Estimators

The IV method is used to analyze the data with an endogenous regressor (an explanatory variable related to unobservable error terms). This endogeneity may be caused by different factors such as mismeasured regressors, sample selection bias, and heterogeneity across individuals (Card, 1995; Heckman & Vytlacil, 1998). The IV method aims to use an additional instrument variable Z (at least one), excluded from the outcome equation, but this variable is an explanatory one in the decision rule equation. Based on Equations 1, 2, and 3, these two assumptions may be described as:

A4: Conditional on X, Z is not associated with the unobservables (V, U^0) and (V, U^1).

A5: Conditional on X, the decision rule, Equation 3 is a non-constant function of Z.

Assumption A4 means that Z can only affect the outcome variable by means of the participation decision (Blundell & Costa Dias, 2002).

Under the homogeneous effects assumption, which assumes that the treatment effects are constant across individuals, the IV method has alternative procedures that can be used with treatment effects α. The first choice may be to estimate treatment effect α from variation in the participation decision correlated with Z such that $\widehat{\alpha}_{\mathrm{IV}} = \dfrac{\operatorname{cov}(y_i, Z_i)}{\operatorname{cov}(d_i, Z_i)}$.

The other alternative option is to estimate the outcome equation (Equation 4) directly. Under the assumption of homogeneity, Equation 4 may be re-written as:

$$Y = \mathrm{g}^0(X) + \alpha D + U \quad ,$$

given assumption A4, the expectation of outcome is:

$E(Y \mid X, Z) = g^0(X) + \alpha P(D = 1 \mid X, Z)$. The IV estimator may be written as:

$$\alpha_{\mathrm{IV}} = \frac{\mathrm{E}(Y \mid Z = z) - \mathrm{E}(Y \mid Z = z + \delta)}{\mathrm{P}(D = 1 \mid Z = z) - \mathrm{P}(D = 1 \mid Z = z + \delta)} \quad ,$$

where assumption A5 holds. Then there are at least two values of Z, which are z and $z + \delta$, such that the denominator is non-zero (Blundell & Costa Dias, 2002).

In contrast with the heterogeneous model, the outcomes differ across individuals. An additional assumption needs to be added in order to identify the treatment effect—A6: The information from the idiosyncratic component of the treatment effect cannot be used to decide whether or not individuals participate in the training.

However, the ATE or TTE cannot be identified based on heterogeneity because the difference between the two groups' average outcomes may be due to unobservables. Imbens and Angrist (1994) propose alternative treatment estimators to solve this problem.

The so-called local average treatment effect (LATE) estimators may be obtained from a local change in instrument Z. According to another strengthened assumption:

A7: Conditional on X , the decision rule is a non-trivial monotonic function of Z .

The LATE may be described as:

$$\alpha_{\mathrm{LATE}}(X_{\mathrm{i}}, z, z+\delta) = \mathrm{E}(Y_{\mathrm{i}}^{1} - Y_{\mathrm{i}}^{0} \mid X_{\mathrm{i}}, \mathrm{D}_{\mathrm{i}}(z) = 0, \mathrm{D}_{\mathrm{i}}(z+\delta) = 1)$$

$$= \frac{\mathrm{E}(Y_{\mathrm{i}} \mid X_{\mathrm{i}}, z+\delta) - \mathrm{E}(Y_{\mathrm{i}} \mid X_{\mathrm{i}}, z)}{\mathrm{P}(D_{\mathrm{i}} = 1 \mid X_{\mathrm{i}}, z+\delta) - \mathrm{P}(D_{\mathrm{i}} = 1 \mid X_{\mathrm{i}}, z)},$$

and this LATE parameter shows how individuals benefit from the margin of participation for a given value of Z (Heckman & Vytlacil, 1999, 2000). Heckman and Vytlacil (1999, 2000, 2004) present an alternative treatment effect parameter, the marginal treatment effect (MTE), if taking the limits when $\delta \to 0$:

$$\alpha_{\mathrm{MTE}}(X_{\mathrm{i}}, z) = \left. \frac{\partial \mathrm{E}(Y \mid X_{\mathrm{i}}, Z)}{\partial \mathrm{P}(D = 1 \mid X_{\mathrm{i}}, Z)} \right|_{Z=z},$$

in which the MTE parameter measures the treatment effect for an infinitesimal change in Z .

The Empirical Studies Using Non-experimental Estimators

Since the evaluation of training programs has earned much attention, the focus is mostly on whether or not the evaluation problem resulting from non-random assignments of participants may be eliminated by econometric estimators using appropriate non-experimental data. In the last three decades, plenty of approaches described in the literature have solved the evaluation problems that arise primarily from selection bias.

The studies presented below clarify alternative approaches to correcting the bias and provide empirical evidence for the comparison of the use of experimental and non-experimental data.

LaLonde (1986) follows Hendry's (1980) and Leamer's (1983) studies in constructing a model for testing the reliability of a non-experimental analysis by comparing the estimates with the results from the experimental data. He analyzes the National Supported Work Demonstration (NSW), which was a temporary training program designed for disadvantaged workers in the United States. This study uses 6,616 randomly assigned observations of an experimental sample from AFDC (Aid for Families with Dependent Children). Earnings were the outcome variables collected before, during, and after participation. LaLonde supposes that the experimental controls and treatments were not affected by the treatment. The findings show that pre-treatment earnings in 1975 and post-treatment earnings are almost the same. LaLonde adopts Heckman's two-step estimation to analyze the estimates with the non-experimental data drawn from the Panel Study of Income Dynamics (PSID) and the Current Population Survey-Social Security Administration (CPS-SSA). These non-experimental estimates show that the treatment has a positive effect on earnings. LaLonde reveals that the comparison group collected from the non-experimental samples significantly affects the robustness of the estimates.

Heckman et al. (1997) and Heckman, Ichimura, Smith, and Todd (1998) argue that LaLonde's comparison groups from the non-experimental data are misapplied as a result of mis-identifying the required parameters. The counterfactual from LaLonde's model misrepresents the treated, had they not participated. The major problems in LaLonde's design are: comparison groups were not collected from a similar local labor market, data on the treated and untreated states were drawn from different databases, and there is insufficient identification across individuals from data (Blundell & Costa Dias, 2002; Heckman et al., 1997). Smith and Todd (2001) reanalyze the same data used in LaLonde's study and present a measure of the bias from a comparison of the non-experimental and experimental controls. Their studies suggest that the use of propensity-score matching estimators can improve estimation bias if only the cross-section data are available.

To eliminate the non-experimental estimation bias as conventionally measured, Heckman et al. (1997) and Heckman, Ichimura, and Todd (1998) apply a matching method combined with the difference-in-differences estimators to identify comparison groups that may be collected in the same labor market. They evaluate the adequacy and performance of the non-experimental matching approaches from the information and data under the Job Training Partnership Act (JTPA). Based on this procedure, the total estimation bias $\mathrm{B}(\mathrm{P}(X)) = \mathrm{E}(Y^0 \mid \mathrm{P}(X), D=1) - \mathrm{E}(Y^0 \mid \mathrm{P}(X), D=0)$, as mentioned above in the matching estimators, may be decomposed into three parts: the non-overlapping support of X, the misjudgment on the common support, $\mathrm{S}(X)$, and the selection bias from unobservables. The researchers use the estimated probability for the matching procedure in constructing the controls and eligible non-participants and show that the non-parametric conditional difference-in-differences estimators can produce estimates as consistent as the results from the index-sufficient sample selection model.

However, due to these various correction estimation methods, the empirical studies show variance in program effects from cohort to cohort. Even based on the same cohort or database, the estimated training effects are still very different. There is a good illustration of the difference in estimates in the evaluation of the 1976 Comprehensive Employment and Training Act (CETA). Several empirical studies evaluating the 1976 CETA present estimates of increases in post-program annual earnings that vary from -$1,533 to $1,638 for white male participants and from $24 to $1,286 for white female participants (Ashenfelter & Card, 1985; Bassi, 1983, 1984; Dickinson, Johnson, & West, 1986; Geraci, 1984; Westat, 1981, 1984).

These studies show substantial differences in the methodology used to correct selection bias. Bassi (1983) and Geraci (1984) use the same comparison group as Westat (1981). The comparison group is created using stratified matching methods, which utilize factorial combinations of selected variables to choose a sub-sample. Bassi (1983) also develops a fixed-effect model to correct selection bias. Westat (1981) uses weighted least squares to estimate training effects. In a later series of reports, Westat (1984) conducts specific comparison groups for different activities in order to enhance the matching procedure to produce a better match. Geraci (1984) uses weighted least squares similar to those found in Westat's studies, but he also conducts Heckman's two-step method to correct the selection bias arising from the presence of individuals with zero earnings. Dickinson et al. (1986) use a regression model similar to that developed by Westat (1984), but they also conduct a comparison group derived from the nearest-neighbor, matching for bias correction. In contrast with the above studies considered here, Ashenfelter and Card (1985) develop a time-series model of the comparison group's earnings, but they exclude the explanatory variables used in other studies mentioned here such as age, race, gender, and schooling. They use a difference-in-differences estimator on the basis of the before-after comparability of the groups to deal with the autocorrelation in the model.

Recent empirical studies evaluating the training programs under JTPA also provide a methodological comparison of the performance of alternative estimation approaches. Heckman et al. (1997) attempt to assess the adequacy of alternative matching procedures in constructing the appropriate estimators. They develop a conditional difference-in-differences estimator with an additional matching procedure. This particular DID estimator is consistent with the index-sufficient sample selection model. They also examine the different effects of various comparison groups drawn from the eligible non-participants in the JTPA research design, the eligible sample from the Survey of Income Program Participation (SIPP), or the program no-shows. Their study reveals that the comparison group from the no-shows affords the smallest earning estimation bias as compared with the other two comparison groups.

Raphael and Stoll (2004) follow Heckman et al.'s (1997) methodology for correcting estimation bias to construct a specific comparison group. They use individuals who are eligible for JTAP services in the state of Massachusetts during the late 1990s but who did not participate in the service (i.e., the no-shows group) as a comparison group. Then the combination of the difference-in-differences estimators and a probabilistic matching approach is used to reduce the estimation bias. In contrast with the JTPA services on earnings effects, which show 10% for females and 5% for males from the analysis of National JTPA experiments, Raphael and Stoll's (2004) estimates show an approximately 25% increase in annual earnings two and one half years after participation. However, a strong local economy and labor market may account for this rise. If the comparison group is chosen from SIPP or CPS, then these estimates may be underestimated. Moreover, Heckman and Smith (1998) and Heckman et al. (1999) present a structural model that is built on the simulated data. The simulated data are based on an individual's decision whether or not to participate. Their findings show that the DID estimator shows the smallest bias as compared with the other two estimators, including the simple cross-section difference estimator and IV estimator.

Summary

This chapter summarizes alternative econometric estimation methods for correcting the evaluation problem. The major methods include Heckman's two-step estimation, instrumental variable (IV) methods, difference-in-differences method, and matching method. Based on different parameters that need to be estimated, each approach has its own assumption and data requirements. The robustness of the estimates of the alternative estimation methods varies. Whether the estimation method can correct the estimation bias or not depends on the data available and the parameter with which analysts are concerned.

If the longitudinal data and repeated cross-section data are available, the difference-in-differences estimators may be applied to estimate the program effects under the requirement of the additive specification of the error term. If either longitudinal or cross-section data are available, then an alternative choice is the matching estimator. However, the reliability and robustness of the matching estimator depend on whether the individual information collected from the treated and untreated is enough or not (Blundell & Costa Dias, 2002).

In comparison with the experimental analysis, the methods mentioned above contribute to the estimation bias correction if experimental data are not available. For example, a number of studies (Ashenfelter & Card, 1985; Bassi, 1983, 1984; Heckman et al., 1997; LaLonde, 1986) find that non-experimental procedures developed to correct the problem of selection bias can show large variability in the estimated effectiveness of training. These widely varying estimates are often quite different from experimentally based estimates from the same data.

The non-experimental data are easily misapplied due to the misidentification of required parameters. For example, LaLonde (1986) produces a comparison group; this counterfactual misrepresents the treated had they not participated (Heckman et al., 1997; Heckman et al., 1998). The major problems in LaLonde's design are criticized on two bases: comparison groups were not collected from a similar labor local market, and the identification across individuals from data may not have been sufficient. To amend these drawbacks of the identification of the required parameters, several factors can help non-experimental methods correct the misrepresentation. These factors include the similarity of the unobservable and observable characteristics of the participants and the comparison group, and use of the same selection rules for participants and comparison groups in a similar local labor market. However, the trade-off limitation still exists due to the availability of data and the program parameters of interest.

Chapter 3

Methodology

The purpose of this study is to evaluate the effects of participation in school-based learning (SBL) programs and to compare the different results by the use of alternative estimation methods and bootstrap analysis. This chapter provides a description of the methodology, which includes information about data, sample construction, variables, and data analysis.

Data

The data examined in this study were collected from people sampled for the National Longitudinal Survey of Youth 1997 (NLSY 97), the latest surveys sponsored by the U.S. Bureau of Labor Statistics (BLS). The NLSY 97 is designed to represent the civilian, non-institutional population of the United States who were born between 1980 and 1984 and were between the ages of 12 and 16 by the end of December 31, 1996. The sample of the NLSY 97 includes 8,984 individuals, originating from 6,819 unique households, who have been interviewed annually since 1997. As of today, seven rounds of data for the NLSY 97 survey are available to the public (U.S. Department of Labor, 2005).

Sample Construction

The data analyzed in this study are primarily derived from Rounds 1-7 of NLSY 97, which was administered from 1997 to 2003. Table 3.1 shows the sample size, retention rate, and fielding periods in NLSY 97 Rounds 1-7.

Table 3.1
NLSY 97 Sample Size, Retention Rate, and Fielding Period

Round	Fielding period	Cross-section sample		Supplement sample		Total sample	
		Total	Retention rate[a]	Total	Retention rate	Total	Retention rate
1	Feb-Oct 1997 and Mar-May 1998	6748	--	2236	--	8984	--
2	Oct 1998- Apr 1999	6279	93.00%	2107	94.20%	8386	93.30%
3	Oct 1999-Apr 2000	6173	91.50%	2036	91.10%	8209	91.40%
4	Nov 2000-May 2001	6055	89.70%	2026	90.60%	8081	89.90%
5	Nov 2001- May 2002	5919	87.70%	1964	87.70%	7883	87.70%
6	Nov 2002- May 2003	5899	87.42%	1999	89.40%	7898	87.91%
7	Nov 2003- May 2004	5783	85.70%	1973	88.24%	7756	86.33%

Source: National Longitudinal Survey of Youth 1997, Rounds 1-7 (U.S. Department of Labor, 2005).
[a] Retention rate is defined as the percentage of base year (1997) respondents remaining eligible who were interviewed in a given survey year.

The respondents in the NLSY 97 sample consist of two subsamples in the first round: (1) a cross-sectional sample of 6,748 observations, which represent individuals who lived in the United States during the initial survey year of 1997; and (2) a supplemental sample of 2,236 respondents, which is designed to oversample Hispanic and black people living in the United States during the initial survey year of 1997 and born during the same period as the cross-sectional sample. In the cross-sectional sample of 6,748 respondents, the ratio of male to female and non-black to black is 1:1 and 5:1, respectively. Table 3.2 shows the sample size by race and sex from 1997 to 2003 (U.S. Department of Labor, 2005).

Table 3.2
NLSY 97 Sample Size by Subsample, Race, and Sex

	Total sample	Cross-sectional sample			Supplemental sample		
		Cross-sectional total	Black	Non-black	Supplemental total	Black	Hispanic & Mixed
Round 1							
Male	4599	3459	537	2922	1140	632	508
Female	4385	3289	544	2745	1096	622	474
Total	8984	6748	1081	5667	2236	1254	982
Round 2							
Male	4283	3213	504	2709	1070	599	471
Female	4103	3066	517	2549	1037	584	453
Total	8386	6279	1021	5258	2107	1183	924
Round 3							
Male	4170	3144	490	2654	1026	572	454
Female	4039	3029	503	2526	1010	568	442
Total	8209	6173	993	5180	2036	1140	896
Round 4							
Male	4117	3098	485	2613	1019	580	439
Female	3964	2957	489	2468	1007	570	437
Total	8081	6055	974	5081	2026	1150	876
Round 5							
Male	3989	3012	455	2557	977	541	436
Female	3894	2907	478	2429	987	558	429
Total	7883	5919	933	4986	1964	1099	865
Round 6							
Male	3998	2996	466	2530	1002	567	435
Female	3900	2903	486	2417	997	569	428
Total	7898	5899	952	4947	1999	1136	863
Round 7							
Male	3928	2951	460	2491	977	555	422
Female	3828	2832	481	2351	996	565	431
Total	7756	5783	941	4842	1973	1120	853

Source: National Longitudinal Survey of Youth 1997, Rounds 1-7 (U.S. Department of Labor, 2005).

This study is based on data from Rounds 1 to 7 of the NLSY 97. Several criteria have been applied to restrict the sample of this study. First, eligibility for the SBL programs was rather limited for the 8,984 selected for the NLSY 97 sample in Round 1. The SBL problems were presented only to those whose highest educational level is the ninth grade or higher. In Rounds 2 to 6, the SBL questions were asked of any respondents enrolled in school. This reduced the sample size to 4,489 in Round 1. The individuals were also asked about the types of SBL programs in which they participated. The results presented in Table 3.3 show the participation in SBL programs with different rounds. With the second round, the respondents who have left high school may be identified; more observations are then made of the following rounds, and therefore the wage measures may be treated as the outcome variable in the early labor market.

Table 3.3
Participation in School-Based Learning (SBL) Programs from Rounds 1 to 6

Round	Valid answer for SBL participation questions	Different types of SBL programs						
		Career major	Job shadowing	Mentoring	Cooperative education	School-sponsored enterprise	Tech prep	Internship or apprenticeship
1	4489	833	532	234	330	408	351	207
2	7425	1081	610	261	397	239	388	284
3	6552	919	460	177	334	122	264	236
4	5468	1248	776	343	464	398	461	312
5	4489	832	391	163	253	65	198	243
6	3638	628	239	140	178	44	107	248

Source: National Longitudinal Survey of Youth 1997, Rounds 1-7 (U.S. Department of Labor, 2005).

Target Population and Sample

The target population in this study is the civilian, non-institutional youth living in the United States who were born between 1980 and 1984. Based on the design of the variables in this study, Table 3.4 describes the samples used and in so doing identifies the samples available for analysis. Rows 1 to 6 indicate the sample size with information on all available explanatory variables including the respondents’ demographic characteristics and socioeconomic information used in the alternative regression models.

Table 3.4
Sample Construction by Dependent Variable and Alternative Regression Method

Alternative estimation method	Current enrollment in college	Employment	Log total worked hour	Log hourly wage rate
Logit/OLS regression	1,145	2,218	1,888	1,052
Heckman two-step correction	1,145	2,218	1,888	1,052
IV[a](I) estimation	1,145	2,218	1,888	1,052
IV(II) estimation	608	1,288	1,097	709
PSM[b] method	247	381	328	167
Tobit regression	-	-	1,837	-

Source: National Longitudinal Survey of Youth 1997, Rounds 1-7 (U.S. Department of Labor, 2005).
[a] IV= instrumental variable estimation
[b] PSM= propensity score matching

Dependent Variables

To gauge the early labor market outcome of youth in the NLSY 97 after enrolling in the SBL programs, this study uses four dependent variables, including current enrollment in college, employment, total worked hours, and hourly wage rate for those respondents who have ever been enrolled in any SBL programs between 1997 and 2002.

Enrollment in college. This variable refers to whether the respondents are currently enrolled in two-year or four-year colleges or if they have earned two-year or four-year college degrees or graduate degrees. The college enrollment variable is coded 1 for those enrolled in or graduated from college in 2003 and 0 for those who were not.

Employment. This variable measures whether or not the respondents were employed in 2003 after not enrolling in secondary school. The respondents were asked whether they were employed or not. This variable is coded into two categories. Those who are employed in 2003 are assigned 1 and those unemployed are coded 0.

Log total worked hours. This variable is the measure of the total worked hours at employee-type jobs in 2003. Based on the literature regarding examining data for the distribution of worked hours, many researchers note that the worked hours data are skewed, with median worked hours smaller than the mean. Consequently, the transformation of total worked hours data using log-normal distribution is usually used to correct the skewness because log-normal distribution is a skewed distribution that can fit actual worked hours well (Quester & Greene, 1982; Tobin, 1958).

Log hourly wage rate. This variable is the traditional measure of the hourly rate of pay but excludes overtime and performance pay. Similarly, the data for the distribution of wages are also skewed in most research, with median wages smaller than the mean. Consequently, the transformation of wage data using a log-normal distribution is also used to correct the skewness to fit actual wages best (Berndt, 1991).

Independent Variables

This section contains a description of the explanatory variables that represent the observed characteristics, including demographic characteristics, which include age, gender, and race, as well as socioeconomic information such as location and residence, biological mother's schooling, student school achievement, household size, gross household income, and post-high school expectations/aspirations.

Age. The age of the respondents at the interview date in a continuous month scheme and is treated as a continuous variable with a range of 211 months to 290 months during the survey year 2003.

Gender. The variable gender is categorized into male and female. Male and female are dummy coded as 0 and 1, respectively.

Race. The respondent's race and ethnicity identification in NLSY97 Round 1 in 1997 consisted of 2,335 Black, 4,665 Non-black / Non-Hispanic, and 1,984 others. Because of invalid SBL data, this study potentially will lose many observations. Therefore, the variable race is only categorized into Black and Non-black. These two groups are dummy coded as 0 and 1, respectively.

Location and residence. This variable information collected from Round 1 in 1997 describes whether the respondent lived in an urban or rural area. Round 4 in 2000 reported this status again. This variable is dummy coded as 0 and 1 for both survey years.

Armed services vocational aptitude battery for math and verbal score (ASVAB_MV). There are twelve factors in the variable armed services vocational aptitude battery *(*ASVAB). To calculate a composite normed score from the 12 factors, the Department of Defense (DOD) assigned a sampling weight for mathematical knowledge, arithmetic reasoning, word knowledge, and paragraph comprehension in the cohort of NLSY 97. DOD computed the percentile scores for these four major factors to get the final aggregate score which was between zero and 99. This study uses the ASVAB_MV scores as the control variables for school achievement The ASVAB_MV test scores are divided into four quartiles, which represent 0-25%, 26%-50%, 51%-75%, and 76%-100% due to the skewness of the score distribution, respectively. Using that the reference group as the first quartile (0); this variable is then coded as 1, 2, and 3, respectively.

Living with biological mother. This variable information obtained from Round 7 in 2003 describes whether the respondents lived with their biological mother or not. This variable is dummy coded as 0 and 1.

Living with biological father. This variable information obtained from Round 7 in 2003 describes whether the respondents lived with their biological father or not. This variable is dummy coded as 0 and 1.

Household size. This variable information obtained from Round 7 in 2003 describes the number of members in the respondent's household.

Log household gross income. The gross income variable represents the aggregation of non-farm and farm wages, the wages of the respondent's spouse/partner, child support, interest and dividends from stocks or mutual funds, rental income, retirement pension/alimony/Social Security payments, parents' income if the respondent resides with them, monetary gifts (other than allowance) from parents, public support sources, and other income in 2002. The data on the distribution of household gross income are also skewed in most research so the transformation of log-normal distribution is also used to correct the skewness to fit actual income best.

Industry. The industry categories in NLSY97 include manufacturing, retail trade, wholesale trade, and "other". Fifty-eight percent of the respondents are in the "other" section and 31% are in the retail section. Therefore, the variable industry is only categorized into retail and non-retail. These two groups are dummy coded as 0 and 1, respectively.

Work experience. This variable refers to the respondents' average accumulative years worked at any employee-type job between 1997 and 2003. The value of this variable is the average number of the created variables information obtained from Rounds 1 to 7, which reports the annual worked year in the survey year.

Biological mother's schooling. This variable refers to the highest grade completed by the respondents' biological mothers (includes both residential and non-residential mothers). The variable mother's schooling is categorized into: "1st-grade to 11th-grade", "12th-grade", "1st-year college to 4th-year college", and "beyond 4th-year college". Using that the reference group as "beyond 4th-year college", this variable is then coded as 1, 2, and 3, respectively.

Proxy Variables for IV Estimation

Post-high schoolwork expectations. Due to the selection bias problem described previously, the participation decisions may be correlated with some unobservable characteristics. This study adapts the procedure developed by Wooldridge (2002) and Neumark and Rothstein (2003) for using proxy variables as the instrumental variables to correct the selection bias from the unobservable characteristics. Prior to participating in SBL programs, these respondents were asked about their post-high school/work expectations. Based on these expectations, SBL participants may be more likely to enter the labor market or to be enrolled in college. However, these expectations are not correlated with the error term of the underlying characteristics affecting the outcome variables, including wages or total worked hours. The detailed explanation is described in the procedure for the IV estimation. In this study, the respondent's self-reported subjective probability for working over 20 hours per week by age 30, for receiving a high school diploma by age 20, and for having a four-year college degree by age 30 are used.

Data Analysis

Based on the eight research questions and the bootstrap analysis for the comparison of alternative estimates in this study, this section is divided into nine parts. To evaluate the unbiased effects on SBL participation, alternative estimation approaches are adopted to eliminate the selection bias and discover the unobserved heterogeneity across individuals. Next, the comparison of the alternative estimates by the bootstrap procedure is described.

Research Question One

For this research question, the dependent variable is the respondents' college enrollment status, which shows discrete values—i.e., yes or no. To build a response model that represents the binary discrete phenomena, the logistic regression model is the standard technique and the dependent variable equates "no" with 0 and "yes" with 1 (Greene, 2000; Pampel, 2000). Next, selection bias correction approaches including Heckman's two-step correction, two types of IV estimation, and PSM method are presented.

Logit model. In this research question, to evaluate the effects of predictor (independent) variables on enrollment in college, the probability of enrollment status is treated as a dichotomous choice—i.e., enrolled or not. Using this dependent variable, the logistic transformation is applied to the linear model. Assume that each individual has a probability of enrolling in college, Pc_{it}, and this probability needs to be estimated. The odds of college enrollment are the ratio of Pc_{it} to $1-Pc_{it}$. The logistic transformation is the logit dependent variable:

$$L = \ln[Odds] = \ln[Pc_{it}/(1-Pc_{it})].$$

If the relationships between the observed demographic and socioeconomic characteristics M_i and the logit dependent variable L are assumed to be linear, this implies that the association between odds and M_i are non-linear, which means:

$$\ln[\text{odds}] = \ln[Pc_{it}/(1-Pc_{it})] = \delta_t \cdot M_i + \theta_t \cdot Ps_{i0} + \gamma_{it},\ \text{t} > 0, \qquad (5)$$

$$\text{Odds} = Pc_{it}/(1-Pc_{it}) = e^{\delta_t \cdot M_i + \theta_t \cdot Ps_{i0} + \gamma_{it}},$$

$$Pc_{it} = \frac{e^{\delta_t \cdot M_i + \theta_t \cdot Ps_{i0} + \gamma_{it}}}{1+e^{\delta_t \cdot M_i + \theta_t \cdot Ps_{i0} + \gamma_{it}}} = \frac{e^{L(M,Ps)}}{1+e^{L(M,Ps)}},$$

where M_i represents control (independent) variables that represent observed exogenous factors and individual characteristics including age, gender, race, location and residence, ASVAB_MV, whether or not living with biological mother, whether or not living with biological father, household size, log household gross income, industry and work experience, and γ_{it} represents the unobservable characteristics. Ps_{i0} is a binary variable that depends on both observed characteristics N_i, including age, gender, race, location and residence, biological mother's education, ASVAB_MV, log household gross income, and unobserved characteristics φ_{i0}. Ps_{i0} = 1 indicates those individuals who have ever been enrolled in any SBL programs between 1997 and 2002 but who exited in the subsequent round or are never enrolled again; $t = 0$ represents the time at which the participation occurs. The SBL program participation equation in this research question may be written as:

$$Ps_{i0} = \omega_0 N_i + \varphi_{i0} \,. \tag{6}$$

In this logit model, the effect of each independent variable on the odds may be derived from the exponentiated coefficients, the odds ratio—i.e., $e^{coefficient}$. Therefore, the estimates of e^{θ_t} represent the mean effect of SBL program participation in period t. This simple logit model can summarize the ratio of odds for the individuals who participate in an SBL program to the odds for the reference group, or those who do not participate. The comparison group consists of individuals assumed to be comparable to participants but who had not participated in the program. The comparison group here is identified by the rule that individuals who have access to SBL programs and have been told the program policy and content of the courses, but they still did not participate in them.

However, it is very possible to misinterpret the logistic regression coefficients due to the small odds from the regression analysis. Therefore, the effects on log odds need to be translated into the effects on probabilities. The effects on the probabilities may be identified at a particular value such as the mean value of the dependent variable. If the independent variable is continuous, the partial derivative represents the percent change in probability for an infinitely small change in the independent variable (e.g., the slope of the tangent line of the logistic cure). The partial derivative for the variable Ps_{i0}, the marginal effect, for example, may be described as:

$$\triangle Pc_{it} = \frac{dPc_{it}}{dPs_{i0}} = \theta_t * Pc_{it} * (1 - Pc_{it}) .$$

However, in this study, the partial derivative does not work best with the independent variable that dummies the participation decision. The dummy variable that represents whether or not the respondents participate in the SBL programs is discrete and the change in probabilities occurs from 0 and 1, which makes the partial derivative less understandable. To solve the discontinuity, Pampel (2000) suggests the following formula to approximate the partial derivative of the coefficient for a dummy variable:

$$L_0 = \ln[Pc_0 / (1 - Pc_0)] ,$$

$$L_d = L_0 + \theta_t ,$$

$$P_d = 1/(1 + e^{-L_d}) ,$$

$$\triangle P = P_d - Pc_0 , \tag{7}$$

where Pc_0 represents the mean of the dependent variable. L_0 is the predicted logit for the dummy variable that the value equals to zero. L_d is the predicted logit for the dummy variable that the value equals to one. θ_t represents the logistic regression coefficient to the predicted logit for the dummy variable that the value equals to one. P_d represents the probability from the predicted logit for the dummy variable that the value equals to one. $\triangle P$ is the effect of the dummy variable on probabilities.

In addition, to evaluate the measures of goodness of the model fit, multiplying the difference in the baseline value (i.e., the baseline log likelihood is derived from the model that includes only the constant term) and the model log likelihood value by –2 is used to evaluate the null hypothesis that all coefficients equal 0. The significance level in the measures of goodness of fit in this study is .05 (i.e., p-value$\leq$ .05).

Heckman's two-step correction. If the estimation of θ_t is unbiased, Equations 8 and 9 show that Ps_{i0} is uncorrelated with ν_{it}. Namely, if $\mathrm{E}(Ps_{i0}\nu_{it}) \neq 0$, $E(\hat{\theta}_t) \neq \theta_t$. As shown in the research on program evaluation mentioned above, this selection bias could happen in practice and it needs to be corrected using alternative estimation methods. The most widely used correction methodology is Heckman's two-step correction (Heckman, 1974, 1979; Heckman et al., 1997). This approach adapts a reduced form of Equations 6 and 5 as shown below:

$$\ln[\text{odds}] = \ln[Ps_{i0}/(1-Ps_{i0})] = \alpha_0 \cdot N_i + \rho_{i0} \quad , \tag{8}$$

$$\ln[\text{odds}] = \ln[Pc_{it}/(1-Pc_{it})] = \kappa_t \cdot M_i + \beta_t \cdot Ps_{i0} + \pi_t \hat{\lambda}_t + \zeta_{it}, \mathrm{t} > 0, \tag{9}$$

where the binary participation variable Ps_{i0} can be estimated by the logistic regression and the predicted participation probabilities are used to create a correction term—$\hat{\lambda}_t$:

$$\hat{\lambda}_t = Ps_{i0} \cdot [(1+e^{-\hat{\alpha}_0 \cdot N_i}) \cdot \ln(1+e^{\hat{\alpha}_0 \cdot N_i}) - \hat{\alpha}_0 \cdot N_i]$$
$$+\ (1-Ps_{i0}) \cdot [e^{\hat{\alpha}_0 \cdot N_i} \cdot \hat{\alpha}_0 \cdot N_i - (1+e^{\hat{\alpha}_0 \cdot N_i}) \cdot \ln(1+e^{\hat{\alpha}_0 \cdot N_i})]\,.$$

Next, $\hat{\lambda}_t$ is used to enter Equation 9 as a regressor and the unbiased estimate of e^{β_t}; the mean effect of training participation in period t can be obtained via the logit model mentioned above.

IV(II) estimation. Another alternative IV estimation to correct for the selection bias is to use the estimated odds of the regressor Ps_{i0} as the instrumental variable (Train, 1994; Wang, 1994). The first step is to estimate the binary participation variable Ps_{i0} by the logistic regression. Next, apply the logit model with the regressor of predicted Ps_{i0}, which was treated as the instrumental variables. Then Equation 8 may be re-written again as:

$$\ln[\text{odds}] = \ln[Pc_{it}/(1-Pc_{it})] = \delta_t \cdot M_i + \theta_t \cdot \widehat{P}s_{i0} + \delta_{it}, t > 0, \tag{10}$$

where δ_{it} is an unobservable, fixed over time for individuals, representing underlying characteristics affecting wages.

IV(II) estimation. Another approach to correcting estimation bias is to find the appropriate proxy variables as the instrumental variables. Equation 5 may be rewritten as:

$$\ln[\text{odds}] = \ln[Pc_{it}/(1-Pc_{it})] = \delta_t \cdot M_i + \theta_t \cdot Ps_{i0} + \xi_t + \psi_{it}, t > 0 \tag{11}$$

where ξ is an unobservable, fixed over time for individuals, representing underlying characteristics affecting wages. The assumption in Equation 10 shows $\mathrm{E}(\varphi \mid Ps, M, \xi) = 0$.

Suppose that $\xi_i = \lambda_i + \theta_{ji} Z_{ji} + \tau_i$, where Z_{ji} are the jth expectations variables and are uncorrelated with τ_i. Wooldridge (2002) and Neumark and Rothstein (2003) suggest that the IV estimation using these proxy variables Z_{ji} can correct for the selection bias on the unobservable characteristics. This study adapts their design and chooses three proxy variables including the respondent's self-reported subjective probability for working more than 20 hours per week by age 30, for receiving a high school diploma by age 20, and for having a four-year college degree by age 30.

PSM method. Based on assumptions A1 and A2 mentioned in chapter 2, the propensity score matching (PSM) method affords a comparison that re-establishes an experimental comparison group such that the counterfactual outcome distribution of the participants and the observed outcome distribution of the non-participants are the same. The basic matching construction is based on a neighborhood $\mathrm{C}(X_i)$, where X_i is the characteristics for individual i.

Neighbors to the treated i are individuals in the comparison group whose characteristics are in neighborhood $\mathrm{C}(X_i)$. There are H_{c} and H_{t} individuals in the comparison group and the treatment group, respectively. Suppose that $A_i = [j \mid X_j \in \mathrm{C}(X_i)]$; this means the individuals in the comparison group who are neighbors to i are those persons j for whom $X_j \in \mathrm{C}(X_i)$. Assume that ω_{ij} is the weight placed on individual j in organizing a comparison group with i, with $\sum_{j=1}^{H_{\mathrm{c}}} \omega_{ij} = 1$ and $0 \le \omega_{ij} \le 1$. The weighted comparison means the outcome for individual i is:

$$\overline{Y}_i^{\mathrm{c}} = \sum_{j=1}^{H_{\mathrm{c}}} \omega_{ij} Y_j^{\mathrm{c}},$$

and the treatment effect that needs to be estimated for an individual I is $Y_i - \overline{Y}_i^{\mathrm{c}}$ (Heckman, LaLonde, & Smith, 1999).

Before choosing appropriate weights, the comparison group for each participant needs to be chosen with a pre-defined criterion of proximity because the explanatory variables X are usually high dimensional. If X is high dimensional, the observations will decrease seriously when in matching. The "propensity score," $\mathrm{P}(X) = \Pr(D = 1 \mid X)$, advocated by Rosenbaum and Rubin (1983, 1984) may be used to adjust the dimensional problem. After $\mathrm{P}(X)$ is estimated, the neighborhood for each treated observation is established by this probability measure. This propensity score may be estimated using the same logit model shown in Equation 8. Next, the weight is used to connect the non-treated with the treated. There are several possibilities in choosing the appropriate weights. In this study, the nearest-neighbor matching estimator is first used to define A_i such that only one j may be closest to X_i in some metric:

$$A_i = \{j \mid \operatorname*{Min}_{j \in \{1, \ldots H_{\mathrm{c}}\}} \| X_i - X_j \| \},$$

where "$\| \ \|$" denotes a metric that describes the distance in the X characteristics space:

$$\| \ \| = (X_i - X_j)' {\textstyle\sum}_{\mathrm{c}}^{-1} (X_i - X_j),$$

where $\sum_{\mathrm{c}}$ is the covariance matrix in the comparison group. The weighting scheme for this nearest-neighbor matching estimator is:

$$\omega'_{ij} = \begin{cases} 1 & \text{if } j \in A_i \\ 0 & \text{otherwise.} \end{cases}$$

For the nearest-neighbor matching estimators, $\omega'_{ij} = 1$ if $j \in A_i$, and otherwise, $\omega'_{ij} = 0$. Consequently, the treatment effect on the treated may be estimated by this average difference across individual i in a general form (Heckman, Ichimura, & Todd, 1997):

$$\hat{\alpha}_{\text{matching}} = \frac{1}{H_{\mathrm{t}}} \omega'_i \sum_{i=1}^{N_{\mathrm{t}}} \{Y_i^{\mathrm{t}} - \overline{Y}_i^{\mathrm{c}}) = \frac{1}{H_{\mathrm{t}}} \sum_{i=1}^{N_{\mathrm{t}}} \{Y_i^{\mathrm{t}} - \sum_{j=1}^{N_{\mathrm{c}}} \omega'_{ij} Y_j^{\mathrm{c}}\}. \tag{12}$$

Research Question Two

For research question two, the dependent variable is whether or not the respondent is employed. For this variable, there are discrete values—i.e., yes or no. The logit model mentioned in research question one may also be applied to this discrete response model. Equations 8 and 9 are also used to estimate the effect of each independent variable on the odds that may be derived from the exponentiated coefficients, the odds ratio. In this logit model, the estimates of e^{θ_t} represent the mean effect of training participation in period t and summarize the ratio of odds for the individuals who participate in the SBL program to the odds for the reference group, those who do not participate. The estimation technique and correction approaches also include logistic regression, Heckman's two-step correction, two types of IV estimation, and PSM method that are used in research question one.

Research Question Three

To study the relationship between the log total worked hours and individual's characteristics and socioeconomic information, the multiple linear regression model is widely used in the analysis. In addition, selection bias correction approaches, including Heckman's two-step correction, two types of IV estimation, PSM method, and Tobit analysis for the censored data, are presented.

Ordinary least square (OLS) regression. Based on the empirical labor economic studies, the behavior of SBL program participants and the effects of participation may be depicted by the following specification (Ashenfelter, 1978; Ashenfelter & Card, 1985;

Berndt, 1991; Friedlander & Greenberg, 1997; Greene, 2000; Heckman, 1974, 1979, 1985; Quester & Greene, 1982):

$$Y_{it} = c_t M_i + b_t Ps_{i0} + \mu_{it} \ , \ t > 0 \, , \tag{13}$$

$$Ps_{i0} = a_0 N_i + \nu_{i0} \, , \tag{14}$$

where Y_{it} is the ith individuals' log total worked hours in period t, with unobserved characteristics μ_{it}. M_i represents exogenous factors and individual characteristics including age, gender, race, location and residence, ASVAB_MV, whether or not living with biological mother, whether or not living with biological father, household size, household gross income, industry, work experience, and log hourly wage rate in period t. Ps_{i0} is a binary variable that depends on both observed characteristics N_i including age, gender, race, location and residence, biological mother's education, ASVAB_MV, log household gross income, and unobserved characteristics ν_{i0}. Ps_{i0} = 1 indicates those individuals who have ever been enrolled in any SBL programs between 1997 and 2002 but who exited in the subsequent round or are never enrolled again; t = 0 represents the time period of participation. In this model, the estimates of b_t represent the mean effect of SBL program participation in period t. This simple OLS regression model can summarize the average differences in the log total worked hours between the SBL program participants and non-participants. The comparison group consists of individuals assumed to be comparable to participants but who had not participated in the program.

In addition, to evaluate the measures of goodness of the model fit, the F ratio was calculated to evaluate the null hypothesis that all coefficients equal 0 in the OLS regression model. The significance level in the measures of goodness of fit in this study is .05 (i.e., p-value $\leq$ .05).

Heckman's two-step correction. If the estimation of θ_t is unbiased, Equations 5 and 6 show that Ps_{i0} is uncorrelated with ν_{it}. Namely, if $\mathrm{E}(Ps_{i0}\nu_{it}) \neq 0$, $E(\hat{b}_t) \neq \hat{b}_t$. As the methodology used in the logit model, this selection bias could be corrected using Heckman's two-step correction. The specification may be rewritten as shown below:

$$Ps_{i0} = \alpha_0 \cdot N_i + \rho_{i0} \quad , \tag{15}$$

$$Y_{it} = \kappa_t \cdot M_i + \beta_t \cdot Ps_{i0} + \pi_t \hat{\lambda}_t + \zeta_{it}, \ \mathrm{t} > 0, \tag{16}$$

where the binary participation variable Ps_{i0} can be estimated by the logistic regression and the predicted participation probabilities are used to create a correction term-- $\hat{\lambda}_t$:

$$\hat{\lambda}_t = Ps_{i0} \cdot [(1 + e^{-\hat{\alpha}_0 \cdot N_i}) \cdot \ln(1 + e^{\hat{\alpha}_0 \cdot N_i}) - \hat{\alpha}_0 \cdot N_i]$$
$$+ \ (1 - Ps_{i0}) \cdot [e^{\hat{\alpha}_0 \cdot N_i} \cdot \hat{\alpha}_0 \cdot N_i - (1 + e^{\hat{\alpha}_0 \cdot N_i}) \cdot \ln(1 + e^{\hat{\alpha}_0 \cdot N_i})] .$$

Next, $\hat{\lambda}_t$ is used to enter Equation 19 as a regressor and the unbiased estimate of β_t, the mean effect of program participation in period t can be obtained via the OLS regression model.

IV(I) estimation. If using the estimated odds of the regressor Ps_{i0} as the instrumental variable (Train, 1994; Wang, 1994), the OLS regression model with the regressor of predicted Ps_{i0} can be used for the IV estimation. Therefore Equation 10 may be rewritten again as:

$$Y_{it} = \delta_t \cdot M_i + \theta_t \cdot \widehat{P}s_{i0} + \delta_{it}, \ t > 0, \tag{17}$$

where δ_{it} is an unobservable, fixed over time for individuals, and represents underlying characteristics affecting wages.

IV(II) estimation. Another approach to correcting the estimation bias is to find the appropriate proxy variables as the instrumental variables. For the continuous dependent variable, logged total worked hours, Equation 11 may be re-written as:

$$Y_{it} = \delta_t \cdot M_i + \theta_t \cdot Ps_{i0} + \xi_t + \psi_{it},\ t > 0, \qquad (18)$$

where ξ is an unobservable, fixed over time for individuals, representing underlying characteristics affecting wages. The assumption in Equation 10 shows $\mathrm{E}(\varphi \mid Ps, M, \xi) = 0$. Next, this study adapts these proxy variables Z_{ji} mentioned in research question one, the respondent's self-reported subjective probability for working more than 20 hours per week by age 30, for receiving a high school diploma by age 20, and for having a four-year college degree by age 30 are used for the instrumental variables.

PSM method. Based on assumptions A1 and A2 mentioned in chapter 2, the propensity score matching (PSM) method affords a comparison that re-establishes an experimental comparison group such that the counterfactual outcome distribution of the participants and the observed outcome distribution of the non-participants are the same. The matching construction is based on a neighborhood $\mathrm{C}(X_i)$, where X_i is the characteristics for individual i. As the procedure mentioned in research question one, for the nearest-neighbor matching estimators, $\omega'_{ij} = 1$ if $j \in A_i$; otherwise, $\omega'_{ij} = 0$. The participation effect on the treated may also be estimated by this average difference across individual i in a general form from Equation 12.

Tobit analysis. In microeconomic data, a very common problem involves occasions where the dependent variable is a censored random variable. For example, if the dependent variables are number of hours worked in the labor force, expenditures on durable goods, or household expenditures on various commodity groups, the empirical literature shows that the censoring occurs because values below zero are not observed (Jarque, 1987; Quester & Greene, 1982; Tobin, 1958). In this research question, the dependent variable is the log total worked hours so the correction of the censoring is presented.

The Tobit model is the econometric model designed for the censored data (Tobin, 1958). The general model specification may be described as:

$$Y_{it}^{*} = b_t X_i + c_t Ps_{i0} + \varepsilon_{it},$$

$$Y_{it} = 0 \text{ if } Y_{it}^{*} \leq 0,$$

$$Y_{it} = Y_{it}^{*} \text{ if } Y_{it}^{*} > 0,$$

where Y_{it} is the ith individuals' log total worked hours in period t, with unobserved characteristics ε_{it}. X_i represent exogenous factors and individual characteristics, including age, gender, race, location and residence, ASVAB_MV, whether or not living with biological mother, whether or not living with biological father, household size, log household gross income, industry, work experience and log hourly wage rate in period t. If the respondent was not employed (worked 0 hours), the dependent variable will be left censored at zero. Therefore, the censored regression needs to consider the conditional mean function as shown below:

$$E(Y_i \mid X_i) = \Phi\left(\frac{b_t X_i}{\sigma}\right) \cdot (b_t X_i + \sigma \cdot \lambda_i) \text{ ,}$$

where $\lambda_i = \dfrac{\phi(b_t X_i / \sigma)}{\Phi(b_t X_i / \sigma)}$,

and ϕ and Φ are the normal probability density and cumulative distribution functions. The marginal effects in the Tobit model may be shown as:

$$\frac{\partial E(Y_{it}^{*} \mid X_i)}{\partial X_i} = b_t \Phi(\frac{b_t X_i}{\sigma}) \text{ .}$$

Research Question Four

To explore the association between the logged hourly wage rate and the respondent's characteristics and socioeconomic information, multiple linear regression is also used in this analysis. The OLS regression model mentioned in research question three may also be applied to this regression model. Equations 13 and 14 are also used to estimate the effect of the covariates including age, gender, race, location and residence, ASVAB_MV, whether or not living with biological mother, whether or not living with biological father, household size, log household gross income, industry, work experience, and log average past hourly wage rate between 1998 and 2002 with the different regressed variable, the log hourly wage rate. This simple OLS regression model is used to summarize the average log hourly wage rate differential between the SBL program participants and non-participants. In addition, selection bias correction approaches include Heckman's two-step correction, two types of IV estimation, and the PSM method.

Research Question Five

Based on the cohort of NLSY 97, there are seven specific types of SBL programs. To study the effects of specific program participation, these seven SBL programs are all dummy coded as 0 and 1 (i.e., participation is coded 1 and non-participation is coded 0), respectively. The reference group is the individuals who never participated in a SBL program between 1997 and 2002.

The logit model mentioned in research question one is still applied to college enrollment with the individual's observable characteristics and socioeconomic information as covariates. The difference is that the seven dummy variables for the seven SBL program, participation is substituted for the initial participation decision variable Ps_{it}. Equation 5 may be rewritten as:

$$\ln[\text{odds}] = \ln[Pc_{it}/(1 - Pc_{it})] = \delta_t \cdot M_i + \theta_{tj} \cdot Ps_{ij0} + \gamma_{it},\ j = 1 \ to\ 7,\ t > 0 .$$

However, the initial SBL participation decision variable is transferred to seven dummy variables. Therefore, all selection bias corrections, including IV estimation, and the PSM method cannot be applied to this model again due to the complexity of the computation. Heckman's two-step correction is the only available correction method.

Research Question Six

The only difference between research questions six and five is the dependent variable. The logit model mentioned in research question five is used to regress employment status on the individual's observable characteristics and socioeconomic information. The seven dummy variables for the participation in the seven SBL programs are substituted for the initial participation decision variable Ps_{it}. In addition, Heckman's two-step correction is the only correction estimation for the selection bias.

Research Question Seven

After recoding the seven dummy variables for the initial SBL participation decision, the *OLS regression model that regresses the respondent's logged total worked hours on the covariates shown in research question three may be rewritten as:*

$$Y_{it} = c_t M_i + b_{tj} Ps_{ij0} + \mu_{it} \ , \ j = 1 \ to \ 7, \ t > 0 .$$

However, due to the complexity of the computation, the correction approach that may be used for the selection bias problems is Heckman's two-step correction. In addition, to correct for censored data, Tobit analysis is presented.

Research Question Eight

The OLS model specification *that regresses the respondent's logged hourly wage rate on the covariates* is the same as for research question five. The difference lies in recoding the seven dummy variables for the initial SBL participation decision. Due to the complexity of the computation, no correction estimation may be available for the selection bias problems.

Bootstrapping Linear Regression Models

In this research, alternative regression correction models are used to explore the best-unbiased estimates due to selection bias. However, what criteria may be used in judging the accuracy of a regression analysis? This study attempts to use a bootstrap algorithm to sort out the conformity of the correction techniques for selection bias.

In basic bootstrapping methodology, if the population distribution is unknown, the values in a random sample are the best approximation to the distribution, and resampling the sample is the best access to what may be expected from resampling the population (Davison & Hinskley, 1997; Efron, 1979, 1983; Efron & Tibshirani, 1993). Specifically, in applying the bootstrap to analyze a linear regression model, suppose that the linear regression model may be described as:

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \varepsilon_i ,$$

where the regressor $\mathbf{x}_i$ is a $1 \times p$ vector $\mathbf{x}_i = (x_{i1}, x_{i2,\ldots} x_{ip})$, and ε_i is the error term that is assumed to be a random sample from an unknown distribution F with expectation 0. The OLS estimate may be expressed as:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} . \tag{19}$$

The answer for the accuracy of the estimated parameter vector $\hat{\boldsymbol{\beta}}$ may be found in the estimated standard errors for the components of $\hat{\boldsymbol{\beta}}$, $\hat{s}(\hat{\beta}_j)$:

$$\hat{s}(\hat{\beta}_j) = \hat{\sigma}_F\sqrt{G^{jj}} \text{ or } \bar{\sigma}_F\sqrt{G^{jj}} ,$$

where $\sigma_F^2 = V_F(\varepsilon)$, $\mathbf{G} = \mathbf{X}^T\mathbf{X}$ with $g_{hi} = \sum_{i=1}^{n} c_{ih}c_{ij}$, and $\hat{\sigma}_F = [\sum_{i=1}^{n}(y_i - \mathbf{x}_i\boldsymbol{\beta})^2 / n]^{1/2}$.

In contrast with the OLS estimate derived from Equation 19, the bootstrap OLS estimate $\hat{\boldsymbol{\beta}}^*$ may be expressed as:

$$\hat{\boldsymbol{\beta}}^* = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}^*,$$

where $\mathbf{y}^*$ may be derived from the empirical distribution $\hat{P} = (\hat{\boldsymbol{\beta}}, \hat{F})$. $\hat{F}$ is an empirical distribution of the $\hat{\varepsilon}_i$, $\hat{\varepsilon}_i = y_i - \mathbf{x}_i\hat{\boldsymbol{\beta}}$. $\hat{F} \rightarrow (\varepsilon_1^*, \varepsilon_2^*, ..., \varepsilon_n^*) = \varepsilon^*$. Each ε_i^* equals any one of the n values $\hat{\varepsilon}_j$ with probability $1/n$. The ideal bootstrap standard error estimate may be shown as:

$$V(\hat{\boldsymbol{\beta}}^*) = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T V(\mathbf{y}^*)\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1} = \hat{\sigma}_F^2(\mathbf{X}^T\mathbf{X})^{-1},$$

Since $V(\mathbf{y}^*) = \hat{\sigma}_F^2\mathbf{I}$, therefore, $\hat{s}_\infty(\hat{\beta}_j) = \hat{\sigma}_F\sqrt{G^{jj}}$. This deduction shows that the ideal bootstrap estimate of standard error for $\hat{\beta}_j$ can approximate the same value derived from Equation 19.

In this study, the paired bootstrap is used to produce the variance and bias estimation for the comparison of the alternative linear regression corrections (Efron & Tibshirani, 1993; Shao & Tu, 1995). Suppose that the probability model $P \rightarrow z$ for a linear regression model may be described as $P = (\boldsymbol{\beta}, F)$, where $\mathbf{z}_i = (\mathbf{x}_i, y_i),\ i = 1, ...n$. The basic algorithm is to estimate the joint distribution of $(\mathbf{x}_i, y_i)$ and the empirical distribution function putting mass n^{-1} to $(\mathbf{x}_i, y_i),\ i = 1, ..., n$. Therefore, the bootstrap data sets $\mathbf{z}^*$ for the regression model equal $(\mathbf{z}_1^*, \mathbf{z}_2^*, ..., \mathbf{z}_n^*) = \{(\mathbf{x}_{i1}, y_{i1}), (\mathbf{x}_{i2}, y_{i2}), ..., (\mathbf{x}_{in}, y_{in})\}$, where $i_1, i_2, ..., i_n$ is a random sample of the integers 1 through n. Efron and Tibshirani (1993) and Cole (1999) suggest that the number of repeating bootstrapping procedures be between 200 and 500 for the empirical estimation of the standard error. Therefore, this study conducts 200-time and 500-time bootstrapping procedures to obtain the resampled estimates for the comparison of alternative linear regression model corrections

Chapter 4

Findings

This chapter reports the research results. The purpose of this study is to estimate the labor market outcomes of participation in school-based learning (SBL) programs with the alternative estimation methods. Alternative regression estimates of the effects of SBL program participation on college enrollment, employment, log total worked hours, and log hourly wage rate are presented in this study. The results are organized according to the research questions.

Research Question One

Q1: Do college enrollment outcomes vary among youth from the NLSY 97 by school-based learning (SBL) program participation?

Research Question Two

Q2: Do employment outcomes vary among youth from the NLSY 97 by school-based learning (SBL) program participation?

Table 4.1 shows whether or not the college enrollment and employment outcomes of U.S. youth in 2003 varied statistically by SBL program participation. Estimates of college enrollment and employment outcomes associated with school-based learning (SBL) program participation are reported in Table 4.1.

After reporting the means and standard errors, the first set of estimates contains the odds ratio and marginal effect evaluated at the mean of the dependent variable with independent variables (the initial control variables) in the Logit model, followed by the estimates derived from alternative selection bias corrections.

In Table 4.1, at an alpha level of .05, for the likelihood of enrolling in college according to the Logit model, SBL program participants are not significantly more likely than non-participants to enroll in college. Compared with the regression estimates from the Logit model, when the IV(I) estimation is adopted, SBL participants are 0.22 times significantly less likely than non-participants to enroll in college.

However, it is very possible to misinterpret the logistic regression coefficients due to the small odds from the regression analysis. Therefore, the effects on the log odds need to be translated into the effects on probabilities. $\vartriangle P$ is the effect of the dummy variable that represents whether or not the respondents participated in the SBL programs on probabilities. Therefore, if evaluated at the mean of the dependent variable, enrollment in college, SBL program participants have a .35 lower probability of enrolling in college than non-participants, at an alpha level of .05.

In contrast with college enrollment, all estimates derived from the regression models that regress the employment outcome on SBL program participation with or without the selection bias corrections are not statistically significant, $p > .05$.

Table 4.1
Logistic Regression Analysis Estimating the Variation in College Enrollment and Employment of the Youth in 2003 in the United States from the NLSY 97 Data by School-Based Learning (SBL) Program Participation

	Current enrollment in college	Employment
Mean of dependent variable	0.72	0.75
(SE)	0.45	0.43
n	1,145	2,218
	Logit model	
Odds ratio	1.58	0.83
(95% CI)	(0.71, 3.52)	(0.63, 1.11)
$\triangle P$	0.08	-0.04
	Heckman's two-step correction	
Odds ratio	0.27	0.77
(95% CI)	(0.06, 1.23)	(0.35, 1.68)
$\triangle P$	-0.30	-0.05
	IV(I) estimation	
Odds ratio	0.22*	0.89
(95% CI)	(0.06, 0.85)	(0.38, 2.11)
$\triangle P$	-0.35	-0.02
-2 log likelihood	1,358.62	2,420.54
df	14	14
p	<.001	<.001
	IV(II) estimation	
Mean of dependent variable	0.65	0.77
(SE)	0.48	0.42
n	608	1,288
Odds ratio	2.22	4.22
(95% CI)	(0.75, 6.56)	(0.60, 1.29)
$\triangle P$	0.13	-0.03
-2 log likelihood	787.54	1,348.76
df	15	15
p	0.08	<.001

Table 4.1 *(Continued)*

	Current enrollment in college	Employment
	PSM method	
Mean of dependent variable	0.76	0.75
(SE)	0.43	0.43
n	247	381
Odds ratio	3.35	0.90
(95% CI)	(0.30, 37.98)	(0.39, 2.05)
ΔP	0.18	-0.02
-2 log likelihood	271.59	421.21
df	14	14
p	<.01	<.001

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).
Note. All estimates are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.
$^*p < .05$

Research Question Three

Q3: What is the mean effect of school-based learning (SBL) program participation as measured by the log total worked hours for youth from the NLSY 97?

Table 4.2 shows the mean effects of school-based learning (SBL) program participation on the log total worked hours of U.S. youth in 2003 with initial and expectation proxy controls, by the OLS regression, Heckman's two-step correction, IV(I) estimation, IV(II) estimation, PSM method, and Tobit analysis, respectively.

After reporting the means and standard errors, the first set of estimates is the coefficients of the SBL participation variable and 95% confidence interval from the OLS regression, followed by the estimates derived from the alternative correction approaches.

In Table 4.2**,** the fit criterion, the sum of squared residuals, provides a measure of goodness-of-fit for the OLS regression, Heckman's two-step correction, IV(I) estimation, IV(II) estimation, and the PSM method. All of these regression models are highly significant ($F = 22.02$, $df = 15$, $p < .001$; $F = 20.68$, $df = 15$, $p < .001$; $F = 22.05$, $df = 15$, $p < .001$; $F = 11.82$, $df = 16$, $p < .001$; $F = 3.96$, $df = 15$, $p < .001$).

With an alpha level of .05, OLS regression estimates in Table 4.2 show that SBL program participants are not significantly more likely than non-participants to have a greater number of total worked hours in 2003. When the Tobit regression is used, the estimates show that SBL program participants are more likely than non-participants to have 13% lower total worked hours.

Research Question Four

Q3: What is the mean effect of school-based learning (SBL) program participation as measured by the log hourly wage rate for youth from the NLSY 97?

Earlier research shows that the youths' wage differential is small in the early labor market (Card & Krueger, 1992; Gardecki & Neumark, 1998; Neumark, 2002; Neumark & Rothstein, 2003). Therefore, a 90% confidence interval is used for the two regression models on the log hourly wage rate outcome.

In Table 4.2, for comparison with total worked hours, the estimates derived from the OLS regression model that regress the log hourly wage rate outcome on SBL program participation are not statistically significant, $p > .10$. When Heckman's two-step correction is used, the estimates show that SBL program participants are more likely than non-participants to have a 17% higher hourly wage rate.

Table 4.2
OLS Regression, Heckman's Two-Step Correction, IV(I) Estimation, IV(II) Estimation, PSM Method, and Tobit Regression Estimates of the Mean Effects of School-Based Learning (SBL) Program Participation on the Log Total Worked Hours and Log Hourly Wage Rate of the Youth in 2003 in the United States from the NLSY 97 Data

		Log total worked hours	Log hourly wage rate[a]
		OLS regression	
Mean of the total worked hours / hourly wage rate		1,355.39	10.06
(SE)		864.93	5.49
n		1,888	1,052
b		-0.11	0.02
(95% CI)		(-0.17, 0.05)	(-0.04, 0.09)
	R^2	0.15	0.21
	F, df	22.02, 15	18.52, 15
	p	<.001	<.001
		Heckman's two-step correction	
b		-0.26	0.17*
(95% CI)		(-0.68, 0.15)	(0.001, 0.33)
	R^2	0.15	0.21
	F, df	20.68, 16	17.53, 16
	p	<.001	<.001
		IV(I) estimation	
b		-0.33	0.13
(95% CI)		(-0.78, 0.12)	(-0.05, 0.32)
	R^2	0.15	0.21
	F, df	22.05, 15	18.60, 15
	p	<.001	<.001
		IV(II) estimation	
Mean of the total worked hours / hourly wage rate		1,412.33	10.36
(SE)		793.59	5.23
n		1,097	709
b		-0.06	0.06
(95% CI)		(-0.27, 0.15)	(-0.03, 0.14)
	R^2	0.15	0.24
	F, df	11.82, 16	13.51, 16
	p	<.001	<.001

Table 4.2 (*Continued*)

	Log total worked hours	Log hourly wage rate[a]
	PSM method	
Mean of the total worked hours / hourly wage rate	1,343.25	11.13
(SE)	1,118.08	7.65
n	328	167
b	-0.14	-0.20
(SE)	(-0.48, 0.20)	(-0.48, 0.08)
R^2	0.16	0.22
F, df	3.96, 15	2.83,15
p	<.001	<.001
	Tobit regression	
Mean of the total worked hours / hourly wage rate	1,355.36	-
(SE)	864.97	-
n	1,837	-
b	-0.13**	-
(95% CI)	(-0.22, -0.03)	-
Log likelihood	-2,017.80	-

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).
Note. All estimates are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.
[a] To eliminate the bias resulted from the youth's small wage differential in the early labor market, a 90% confidence interval is used for this regression model.
*$p < .10$; ** $p < .01$

Research Question Five

Q5: Do college enrollment outcomes vary among youth from the NLSY 97 by the seven specific types of school-based learning (SBL) program participation?

Information sought through research question five focuses on whether or not the college enrollment of U.S. youth in 2003 varied statistically by the seven specific types of

SBL program participation. The estimates for college enrollment outcomes associated with the seven specific types of school-based learning (SBL) program participation are reported in Table 4.3.

After reporting the means and standard errors, the two sets of estimates contain the odds ratio and marginal effect evaluated at the mean of the dependent variable by the Logit model and Heckman's two-step correction for selection bias.

For the significant likelihood of enrolling in college from among those eligible in the logit model, tech prep program participants in Table 4.3 are 1.45 times more likely than non-participants for all SBL programs to enroll in college, at an alpha level of .05. In contrast with the estimates for the odds ratio, if evaluated at the mean of the dependent variable, college enrollment, tech prep program participants have a 0.7 higher probability of being employed than non-participants for all SBL programs.

However, when considering selection bias, the estimates derived from Heckman's two-step correction show no significance.

Table 4.3

Logistic Regression Analysis Estimating the Variation in College Enrollment of the Youth in 2003 in the United States from the NLSY 97 Data by the Seven Specific Types School-Based Learning (SBL) Program Participation

	Current enrollment in college	
	Logit model	Heckman's two-step correction
Mean of dependent variable	0.72	0.72
(SE)	0.45	0.45
n	1,145	1,145
Career major		
Odds ratio	0.94	1.29
(95% CI)	(0.71, 1.26)	(0.28, 5.96)
$\triangle P$	-0.01	0.05
Job shadowing		
Odds ratio	1.27	0.55
(95% CI)	(0.93, 1.72)	(0.10, 2.93)
$\triangle P$	0.05	-0.13
Mentoring		
Odds ratio	1.00	1.57
(95% CI)	(0.70, -1.43)	(0.23, 10.78)
$\triangle P$	-0.0002	0.08
Cooperative education		
Odds ratio	0.73	0.34
(95% CI)	(0.50, 1.06)	(0.06, 2.15)
$\triangle P$	-0.07	-0.2513
School-sponsored enterprise		
Odds ratio	1.07	0.70
(95% CI)	(0.75, 1.54)	(0.11, 4.47)
$\triangle P$	0.01	-0.08
Tech prep		
Odds ratio	1.45**	0.86
(95% CI)	(1.07, 1.98)	(0.16, 4.50)
$\triangle P$	0.07	-0.03
Internship or apprenticeship		
Odds ratio	1.08	2.52
(95% CI)	(0.74, 1.58)	(0.60, 10.69)
$\triangle P$	0.02	0.15
-2 log likelihood	1,358.62	1358.62
df	20	27
p	<.001	<.001

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).
Note. All estimates are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.
**$p < .05$

Research Question Six

Q6: Do employment outcomes vary among youth from the NLSY 97 by the seven specific types of school-based learning (SBL) program participation?

The purpose of research question six is to examine whether or not the employment outcomes of U.S. youth in 2003 varied statistically by the seven specific types of SBL program participation. The estimates for employment outcomes associated with the seven specific types of school-based learning (SBL) program participation are reported in Table 4.4.

After reporting the means and standard errors, the two sets of estimates contain the odds ratio and marginal effect evaluated at the mean of the dependent variable by the Logit model and Heckman's two-step correction for selection bias.

For the significant likelihood of being employed using the logit model, tech prep program participants in Table 4.4 are 0.71 times less likely than non-participants in all SBL program programs to be employed at an alpha level of .05. Internship or apprenticeship program participants in Table 4.4 are 1.28 times more likely than non-participants for all SBL program participants to be employed, at an alpha level of .05.

In contrast with the estimates for the odds ratio, if evaluated at the mean of the dependent variable, employment, tech prep program participants have a 0.07 lower probability of being employed than non-participants for all SBL programs. Internship or apprenticeship program participants have a 0.04 higher probability of being employed than non-participants for all SBL programs.

However, when considering selection bias, the marginal effects of SBL participation derived from Heckman's two-step correction show no significance.

Table 4.4

Logistic Regression Analysis Estimating the Variation in Employment of the Youth in 2003 in the United States from the NLSY 97 Data by the Seven Specific Types School-Based Learning (SBL) Program Participation

	Employment	
	Logit model	Heckman's two-step correction
Mean of the dependent variable	0.75	0.75
(SE)	0.43	0.43
n	2,218	2,218
Career major		
Odds ratio	0.79	0.69
(95% CI)	(0.62, 1.01)	(0.27, 1.77)
$\triangle P$	-0.05	-0.08
Job shadowing		
Odds ratio	1.01	1.02
(95% CI)	(0.77, 1.32)	(0.36, 2.87)
$\triangle P$	0.002	0.004
Mentoring		
Odds ratio	1.12	1.38
(95% CI)	(0.81, 1.56)	(0.40, 4.79)
$\triangle P$	0.02	0.17
Cooperative education		
Odds ratio	1.08	1.17
(95% CI)	(0.79, 1.48)	(0.35, 3.94)
$\triangle P$	0.01	0.03
School-sponsored enterprise		
Odds ratio	1.29	1.44
(95% CI)	(0.94, 1.77)	(0.45, 4.58)
$\triangle P$	0.04	0.06

Table 4.4 *(Continued)*

	Employment	
	Logit model	Heckman's two-step correction
Tech prep		
Odds ratio	0.71*	0.51
(95% CI)	(0.53, 0.95)	(0.17, 1.49)
$\triangle P$	-0.07	-0.15
Internship or apprenticeship		
Odds ratio	1.28*	1.20
(95% CI)	(1.00, 1.63)	(0.47, 3.05)
$\triangle P$	0.04	0.03
-2 log likelihood	2,420.54	2,420.54
df	20	27
p	<.001	<.001

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).
Note. All estimates are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.
*$p < .05$

Research Question Seven

Q7: What is the mean effect of the seven specific types of school-based learning (SBL) program participation as measured by the log total worked hours for youth from the NLSY 97?

An answer for research question seven requires an estimate of the mean effects of SBL program participation on the log total worked hours for U.S. youth in 2003. Three regression models including OLS, Heckman's two-step correction, and Tobit regression are reported in Table 4.5.

After reporting the means and standard errors, the three sets of estimates are the coefficients of the SBL participation variable and the 95% confidence interval for the three regression models.

In Table 4.5, OLS and Heckman's correction models are highly significant (F = 16.14, df = 21, $p < .001$; F = 12.34, df = 28, $p < .001$). At an alpha level of .05, OLS regression estimates show that internship/apprenticeship program participants were more likely than non-participants to have 17% fewer total worked hours in 2003. However, there are no significant estimates in Heckman's correction models when considering the selection bias problem. Due to the correction of the censored data, the estimates derived from the Tobit regression show that internship/apprenticeship program participants are more likely than non-participants to have 20% fewer total worked hours, with an alpha level of .001.

Table 4.5
OLS Regression, Heckman's Two-Step Correction, and Tobit Regression Estimates of the Mean Effects of the Seven Specific Types of School-Based Learning Program (SBL) Participation on the Log Total Worked Hours of the Youth in 2003 in the United States from the NLSY 97 Data

	Log total worked hours		
	OLS regression	Heckman's two-step correction	Tobit regression
Mean of total worked hour	1355.39	1355.39	1,355.36
(SE)	864.93	864.93	864.97
n	1,888	1,888	1,837
Career major			
b	0.05	0.15	0.03
(95% CI)	(-0.08, 0.18)	(-0.35, 0.64)	(-0.04, 0.11)
Job shadowing			
b	-0.01	-0.43	-0.03
(95% CI)	(-0.15, 0.13)	(-0.97, 0.10)	(-0.11, 0.05)
Mentoring			
b	-0.07	-0.06	-0.04
(95% CI)	(-0.24, 0.10)	(-0.71, 0.58)	(-0.14, 0.05)
Cooperative education			
b	0.09	-0.25	0.03
(95% CI)	(-0.07, 0.25)	(-0.86, 0.37)	(-0.06, 0.13)
School-sponsored enterprise			
b	0.04	0.48	-0.02
(95% CI)	(-0.13, 0.20)	(-0.13, 1.09)	(-0.11, 0.06)
Tech prep			
b	-0.02	0.03	-0.02
(95% CI)	(-0.17, 0.13)	(-0.53, 0.58)	(-0.11, 0.06)
Internship or apprenticeship			
b	-0.17**	-0.08	-0.20***
(95% CI)	(-0.30, -0.05)	(-0.57, 0.41)	(-0.27, -0.12)
R^2	0.15	0.16	-
F, df	16.14, 21	12.34, 28	-
p	<.001	<.001	-
log likelihood	-	-	-2005.72

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).
Note. All estimates are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.
**$p < .01$; *** $p < .001$

Research Question Eight

Q8: What is the mean effect of the seven specific types of school-based learning (SBL) program participation as measured by the log hourly wage rate for youth from the NLSY 97?

Table 4.6 shows the mean effects of seven different types of SBL program participation on the log hourly wage rate for U.S. youth in 2003 according to OLS and Heckman's two-step correction. To eliminate the bias resulting from the youth's small wage differential in the early labor market, a 90% confidence interval is used in the two regression models. After reporting the means and standard errors, the two sets of estimates are the coefficients for the SBL participation variable. In Table 4.6, both models are significant ($F = 13.51$, $df = 21$, $p < .001$; $F = 10.34$, $df = 28$, $p < .001$). One of the estimates derived from the OLS regression model that regresses the log hourly wage rate outcome on the seven types of SBL programs participation shows that career major program participants are more likely than non-participants for all SBL programs to have a 6% higher hourly wage rate with an alpha level of .10. When considering the Heckman's correction, internship or apprenticeship program participants are more likely than non-participants for all SBL programs to have a 22% higher hourly wage rate with an alpha level of .10.

Table 4.6

OLS Regression and Heckman's Two-Step Correction Estimates of the Mean Effects of the Seven Specific Types of School-Based Learning Program (SBL) Participation on the Log Hourly Wage Rate of the Youth in 2003 in the United States from the NLSY 97 Data

	Log hourly wage rate[a]	
	OLS regression	Heckman's two-step correction
Mean of hour wage rate	10.06	10.06
(SE)	5.49	5.49
n	1,052	1,052
Career major		
b	0.06*	-0.04
(95% CI)	(0.01, 0.11)	(-0.23, 0.16)
Job shadowing		
b	-0.01	0.09
(95% CI)	(-0.07, 0.05)	(-0.12, 0.30)
Mentoring		
b	-0.05	-0.23
(95% CI)	(-0.12, 0.02)	(-0.49, 0.02)
Cooperative education		
b	-0.03	0.02
(95% CI)	(-0.10, 0.04)	(-0.21, 0.26)
School-sponsored enterprise		
b	-0.04	0.02
(95% CI)	(-0.11, 0.02)	(-0.23, 0.26)
Tech prep		
b	-0.004	-0.07
(95% CI)	(-0.06, 0.05)	(-0.30, 0.16)
Internship or apprenticeship		
b	0.03	0.22*
(95% CI)	(-0.03, 0.08)	(0.02, 0.43)
R^2	0.22	0.22
F, df	13.51, 21	10.34, 28
p	<.001	<.001

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).

Note. All estimates are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.

[a] *To eliminate the bias resulted from the youth's small wage differential in the early labor market, a 90% confidence interval is used for this regression model.*

**p< .10*

Chapter 5

Summary, Discussion and Recommendations

This chapter contains a summary of the results of this study and a discussion of the implications of the findings. Recommendations for future study are also presented.

Summary

The purpose of this study is to use alternative estimation methods to evaluate the effects of U.S. youths' school-based learning (SBL) program participation on early labor market outcomes. The non-experimental database from the NLSY 97 offers detailed data about SBL participation and information on the participants' characteristics and socioeconomic status. However, a regression model using non-experimental data will produce biased estimates because unobservable characteristics related to the participants' labor market outcomes may be related to their SBL program participation decisions. This estimation bias is the so-called selection bias. To solve for the selection bias resulting from unobserved characteristics between the participants and their counterfactual, this study conducts alternative econometric corrections to obtain unbiased estimates.

A review of the literature on estimation correction for program evaluation suggested four major approaches: difference-in-difference method, Heckman's two-step correction, instrumental variable (IV) estimation, and matching method. These approaches construct the counterfactual from the non-experimental data to mimic randomized control and also solve bias resulting from endogeneity. Due to the available data from the NLSY 97, this study considers four methods to correct for the selection bias problem: Heckman's two-step correction, two types of IV estimation, and propensity score matching (PSM) method.

At an alpha level of .05, the findings from the first research question show that SBL program participants are not significantly more likely than non-participants to enroll in college—this finding had no selection bias correction. Rather, when the IV(I) estimation method i adopted, findings reveal that SBL participants are significantly less likely than non-participants to enroll in college. Specifically, if evaluated at the mean of the dependent variable, enrollment in college, SBL program participants have a lower probability of enrolling in college than do non-participants.

In contrast with college enrollment, findings from the analysis of employment and total worked hours outcomes on SBL program participation are not statistically significant with or without selection bias corrections. Rather, only the estimates derived from the method that considers Tobit regression for the correction of the censored data show that SBL program participants have lower total worked hours than non-participants. Due to the evidence that the youths' wage differential is small in the early labor market, the findings from Heckman's two-step correction with an alpha level of .10 show that SBL program participants are more likely to have higher hourly wages than non-participants.

In contrast with research questions one to four, research questions five to eight examine whether college enrollment and employment outcomes for U.S. youth in 2003 varied statistically and look at the mean effects of SBL program participation on the log total worked hours and log hourly wage rate by the seven specific types of SBL program participation.

With an alpha level of .05 for the significant likelihood of enrolling in college, tech prep program participants are more likely than non-participants in all SBL programs to enroll in college. If evaluated at the mean, tech prep program participants have a higher probability of being employed than non-participants in all SBL programs. However, when considering the selection bias, the estimates derived from Heckman's two-step correction show no significance.

For the significant likelihood of being employed, tech prep program participants are less likely than non-participants for all SBL program programs to be employed. Internship or apprenticeship program participants are more likely than non-participants in all SBL programs to be employed. If evaluated at the mean, tech prep program participants have a lower probability of being employed than do non-participants for all SBL programs. Internship or apprenticeship program participants have a higher probability of being employed than do non-participants for all SBL programs. However, when considering the selection bias, the marginal effects of SBL participation derived from Heckman's two-step correction show no significance.

Findings from the estimates show that internship or apprenticeship program participants are more likely to have lower total worked hours than non-participants in 2003. However, there are no significant estimates in Heckman's correction models when considering the selection bias problem. Due to the correction of the censored data by Tobit regression, the results show that internship/apprenticeship program participants have lower total worked hours than non-participants with an alpha level of .001.

Due to the small wage rate differential for youth in the early labor market, the significance level of .10 is used for this outcome variable. The findings derived from the OLS regression model that regresses the log hourly wage rate outcome on SBL program participation show no statistical significance. When Heckman's two-step correction is conducted, the findings reveal that SBL program participants are more likely than non-participants to have higher hourly wage rates. Regressing the log hourly wage rate outcome on the seven types of SBL program participation reveals that career major program participants are more likely to have higher hourly wages than non-participants for all SBL programs. Rather, the findings from Heckman's correction indicate that internship or apprenticeship program participants are more likely than non-participants for all SBL programs to have a higher hourly wage rate.

Discussion

Research Questions One and Five

> *Q1: Do college enrollment outcomes vary among youth from the NLSY 97 by school-based learning (SBL) program participation?*
>
> *Q5: Do college enrollment outcomes vary among youth from the NLSY 97 by the seven specific types of school-based learning (SBL) program participation?*

In terms of the likelihood of college enrollment in 2003 in the initial Logit model, the findings indicate that youths who ever participated in a SBL program are not more significantly likely to enroll in college. Specifically, when considering the seven specific types of SBL programs, tech prep program participants are more significantly likely to enroll in college. These findings are not consistent with previous research using IV estimation (Altonji, 1993, 1995), which suggests that school-to-work (STW) programs reduce the likelihood of college enrollment as a postsecondary career choice. Therefore, if also considering the correction of the selection bias, the finding in this study from the IV(I) estimation indicates consistent results—the youths who have ever participated in any SBL programs are less significantly likely to enroll in college. However, no significance is detected for the seven types of SBL program participation. In addition, a difference exists between this study's finding and the recent study finding by Neumark and Rothstein (2003). They use the NLSY 97 Rounds 1 to 4 to examine the college enrollment outcomes in 2000 and suggest that school-sponsored enterprise program participants may be more significantly likely to enroll in college in 2000. This difference may be due to the latest outcomes in 2003 in this study, which shows that the youth are more likely to approach a transition to postsecondary career choices in the early labor market in the survey year.

Research Questions Two and Six

> *Q2: Do employment outcomes vary among youth from the NLSY 97 by school-based learning (SBL) program participation?*
>
> *Q6: Do employment outcomes vary among youth from the NLSY 97 by the seven specific types of school-based learning (SBL) program*

participation?

All of the findings derived from the regression models that regress the employment outcome on SBL program participation with or without the selection bias corrections are not statistically significant, $p > .05$. When considering the seven specific types of SBL programs, the finding shows that only the tech prep program participants are more significantly likely to be employed in 2003 without the selection bias correction. In contrast with Neumark and Rothstein's findings (2003), they suggest that cooperative education and internship/apprenticeship program participants are more significantly likely to be employed in 2000. This study's correction estimates indicate that SBL program participation does not significantly increase the likelihood of being employed. In a comparison with the youths' SBL participation decisions, based on this study's Logit model with the four bias corrections, the youths' characteristics and socioeconomic information show variation with regard to whether or not they are employed. With an alpha level of .05, older, female, and non-retail industry youth with less household income are more likely to be employed in 2003.

Research Questions Three and Seven

Q3: What is the mean effect of school-based learning (SBL) program participation as measured by the log total worked hours for youth from the NLSY 97?

Q7: What is the mean effect of the seven specific types of school-based learning (SBL) program participation as measured by the log total worked *hours for youth from the NLSY 97?*

All of the findings derived from the linear regression models that regress the log total worked hours outcome on SBL program participation with or without selection bias corrections are not statistically significant, $p > .05$. In this linear regression model, the dependent variable is the log total worked hours in the labor force with a sample size of 1,837. However, 51 observations show no worked hours. Due to the censoring of the dependent variable, the most estimation bias may result from the fact that the values below zero are not observed (Jarque, 1987; Quester & Greene, 1982; Tobin, 1958). Therefore, the finding from Tobit analysis that was designed for the censored data correction (Tobin, 1958) indicates that SBL program participants are more likely than non-participants to have 13% lower total worked hours in 2003. When considering the seven specific types of SBL programs, the finding shows that only the internship or apprenticeship program participants are strongly significantly more likely to have 20% lower total worked hours in 2003, according to the Tobit analysis, $p < .001$.

Research Questions Four and Eight

Q4: What is the mean effect of school-based learning (SBL) program participation as measured by the logged hourly wage rate for youth from the NLSY 97?

Q8: What is the mean effect of the seven specific types of school-based learning (SBL) program participation as measured by the logged hourly wage rate for youth from the NLSY 97?

Specifically, to reduce the bias resulting from the youths' small wage differential in the early labor market, a 90% confidence interval is used for these regression models. The findings derived from the OLS regression model that regresses the log hourly wage rate outcome in 2003 on SBL program participation show no statistical significance. After conducting Heckman's two-step correction, findings show that SBL program participants are more likely than non-participants to have higher hourly wage rate in 2003.

After regressing the log hourly wage rate outcome on the seven types of SBL program participation, findings show that career major program participants are more likely to have higher hourly wages than non-participants for all SBL programs. Rather, the findings from Heckman's correction indicate that internship or apprenticeship program participants are more likely than non-participants for all SBL programs to have a higher hourly wage rate.

In contrast, Neumark and Joyce's study (2001) uses OLS, two selection bias corrections, including school-fixed-effect regression by general linear method (SFC-GLS) and IV correction, to estimate the effects of SBL program participation on the log hourly wage rate outcome in 1997. Their findings show no statistical significance, with an alpha level of 0.05. Differences in the findings may be due to the youths' involvement in the early labor market. The youths may not have really entered the labor market in 1997 because most were still enrolled in secondary school.

Bootstrap and the Comparison of the Linear Regression Estimates

In research questions three, four, seven, and eight, the initial linear regression models are the OLS models with no selection bias corrections. Four other correction models are used to explore the best-unbiased estimates due to selection bias. However, how does one compare all of the estimates for these four different correction methods? This study attempts to use a bootstrap algorithm to sort out the accuracy and robustness of these four correction techniques for selection bias. However, in research questions three and seven, the dependent variable, total worked hours, is a censored variable so the four corrections for selection bias may not be the best methods for assessing the censoring bias. Tobit analysis is the only useful correction method for these two research questions. Therefore, the bootstrap procedure focuses on a linear regression on log hourly wage rate in research question four (since there is only one correction method for research question eight).

In Table 5.1, the 200-time and 500-time bootstrapping results show that the standard error for the resampled estimates from the Heckman's two-step correction estimation is the smallest; the PSM method shows the largest variation in estimates. Therefore, based on the criteria from the bootstrapping, the best selection bias estimation among these four corrections uses the Heckman's two-step correction.

Table 5.1

Bootstrapping Analysis for the Linear Regression of Heckman's Two-Step Correction, IV(I), IV(II) Estimation and Propensity Score Matching (PSM) method Tobit Regression by School-Based Learning Program (SBL) Participation on the Log Hourly Wage Rate of the Youth in 2003 in the United States from the NLSY 97 Data

	β	β_{BOOT}	SE	SE_{BOOT}	Difference[a]	Difference ratio[b]
				B^c=200		
Heckman's two-step correction	0.16664	0.17875	0.1017	0.10152	-0.00177	-1.74%
IV(I) estimation	0.13392	0.12488	0.1133	0.11541	0.01826	16.11%
IV(II) estimation	0.05567	0.05327	0.0495	0.04925	-0.00485	-9.80%
PSM method	-0.1988	-0.18792	0.1696	0.14751	-0.13030	-76.82%
				B=500		
Heckman's two-step correction	0.16664	0.1683	0.1017	0.10137	-0.00324	-3.19%
IV(I) estimation	0.13392	0.13393	0.1133	0.11177	-0.01385	-12.22%
IV(II) estimation	0.05567	0.06337	0.0495	0.04941	-0.00162	-3.27%
PSM method	-0.1988	-0.19969	0.1696	0.14445	-0.14834	-87.46%

Source: National Longitudinal Survey of Youth 1997 Data, Rounds 1-7 (U.S. Department of Labor, 2005).

Note. Estimates β and β_{BOOT} are the coefficient's estimates of the SBL participation variable, which represent the mean effect of program participation.

[a] Difference= $SE_{\mathrm{BOOT}} - SE$;[b] Difference ratio= $(SE_{\mathrm{BOOT}} - SE)/SE$;[c] B=the times that repeat the bootstrapping procedure.

Recommendations for Future Study

Recommendations for future study are organized under three headings: counterfactual construction; measurement of the observable characteristics of the individual and school; and bootstrap in the logistic regression model.

Counterfactual Construction

The methodology challenge in the evaluation of U.S. SBL program participation lies in constructing the ideal counterfactual. A better correction for selection bias is to use experimental data. However, it was not available for this study. Another natural control group would involve comparing the respondents with their before-after outcomes in the labor market. NLSY 97 also did not offer before-after comparable data. Therefore, econometric corrections are the best major methods for constructing the counterfactual and correcting estimation bias. Theoretically, recent studies have developed more correction estimators to handle selection bias, such as local instrumental variables (LIV) (Aakvik, Heckman, & Vytlacil, 2005; Heckman & Vytlacil, 2004). Heckman et al. (1999) also suggest the use of simulated data in constructing a better counterfactual.

Measurement of the Observable Characteristics of the Individual and School

More information should be included and analyzed in the regression model when constructing observable covariates from the transcript data for youth in the NLSY 97. In addition, all schools in the sample may be identified from the 1996 School Administrator's Survey (SAS 96), which is a supplemental collection of information at the school level; however, it is not available as public-use data. Additional information about the youths and their schools should be used in future study.

Bootstrap in the Logistic Regression Model

This study only bootstraps the linear regression model in order to compare variation in predictive effectiveness. For the logistic regression, the assessment of the receiver operating characteristic (ROC) is recommended when measuring the accuracy of the prediction of likelihood by calculating the area under the curve (AUC) in empirical studies (Hanley & McNeil, 1982; Pepe, 2000; Rust & Rao, 1996).

References

Aakvik, A., Heckman, J., & Vytlacil, E. (2005). Estimating treatment effects for discrete outcomes when responses to treatment vary: An application to Norwegian vocational rehabilitation programs. *Journal of Econometrics, 125*(1-2), 15-51.

Altonji, J. G. (1993). The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics, 11*(1), 48-83.

Altonji, J. G. (1995). The effects of high school curriculum on education and labor market outcomes. *The Journal of Human Resources, 30*(3), 409-438.

Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *Review of Economic and Statistics, 60*, 47-57.

Ashenfelter, O., & Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *Review of Economic and Statistics, 66*, 36-43.

Barnow, B. S., Cain, G. G., & Goldberger, A. S. (1980). Issues in the analysis of selection bias. In E. W. Stromsdorfer & G. Farkas (Eds.), *Evaluation studies review annual* (Vol. 5, pp. 43-59). Beverly Hills, CA: Sage Pub.

Barrow, B. S. (1987). The impact of CETA programs on earnings. *The Journal of Human Resources, 22*(2), 157-193.

Bassi, L. (1983). The effect of CETA on the post-programs earnings of participants. *The Journal of Human Resources, 18*, 539-556.

Bassi, L. (1984). Estimating the effects of training programs with nonrandom selection. *Review of Economic and Statistics, 66*, 36-43.

Berndt, E. R. (1991). *The practice of econometrics: Classic and contemporary*. Reading, MA: Addison-Wesley.

Bishop, J., Mane, F., Ruiz, A. (2001). STW in the 1990s. *The CEIC Review, 10*(8), 14-17.

Blundell, R., & Costa Dias, M. (2000). Evaluation methods for non-experimental data. *Fiscal studies, 21*(4), 427-468.

Blundell, R., & Costa Dias, M. (2002). Alternative approaches to evaluation in empirical microeconomics. *Portuguese Economic Journal, 1*(2), 91-115.

Card, D. (2001). Estimating the return to schooling: progress on some persistent econometric problems. *Econometrica, 69*(5), 1127-1160.

Center for Human Resource Research. (2003). *NLSY97 user's guide*. Columbus: The Ohio State University Press.

Cochrane, W., & Rubin, P. K. (1973). Controlling bias in observational studies. *Sankyha, 35,* 417-446.

Cole, S. R. (1999). Simple bootstrap statistical inference using the SAS system. *Computer Methods and Programs in Biomedicine, 60*, 79-82.

David, A. C., & Hinkley, D. V. (1997). *Bootstrap methods and their application.* Cambridge: Cambridge University Press.

Dickinson, K. P., Johnson, T. R., & West, R. W. (1984). An analysis of the impact of CETA programs on participants' earnings. *The Journal of Human Resources, 21*(1), 64-91.

Efron, B. (1979). Bootstrap methods: another look at the jackknife. *Annals of Statistics, 7*, 1-26.

Efron, B. (1983). Estimating the error rate of a prediction rule: Improvements on cross-validation. *Journal of American Statistical Association, 78,* 316-331.

Efron, B. & Tibshirani, R. J. (1993). *An introduction to the bootstrap.* New York, NY: Chapman & Hall.

Eissa, N., & Liebman, J. (1996). Labor supply response to the earned income tax credit. *Quarterly Journal of Economics, 111*, 605-637.

Fisher, R. (1951). *The design of experiments* (6th ed.). London: Oliver and Boyd.

Friedlander, D., Greenberg, D. H., & Robins, P. K. (1997). Evaluating government training programs for the economically disadvantaged. *Journal of Economics Literature, 35*(4), 1809-1855.

Gardecki, R., & Neumark, D. (1998). Order from chaos? The effects of Early labor market experiences on adult labor market outcomes. *Industrial and Labor Relations Review, 51*(2), 299-322.

Geraci, V. J. (1984). *Short-term indicators of job training program effects on long-term participant earnings.* (U.S. DOL No. 20-48-82-16). PUBLICATION INFO?

Greene, W. H. (2000). *Econometric analysis* (4th ed.). Upper Saddle River, NJ: Prentice-Hall.

Gronau, R. (1974). Wage comparisons- a selection bias. *Journal of Political Economy, 82*(6), 1119-1144.

Hanley, J. A. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology, 143,* 29-36.

Heckman, J. (1974). Shadow prices, market wages, and labor supply. *Econometrica, 42*, 679-694.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153-161.

Heckman, J. (1985). Selection bias and self-selection. In *The new Palgrave: a dictionary of economics* (pp. 287-296). Stockton, NY: Macmillan.

Heckman, J. (1997). Instrumental variables: A study of impact behavioral assumptions used in making program evaluations. *The Journal of Human Resources, 32*(3), 441-462.

Heckman, J. (2001). Micro data, heterogeneity and the evaluation of public policy: Nobel lecture. *Journal of Political Economy, 109*, 673-748.

Heckman, J., & Hotz, V. J. (1989). Choosing among alternative nonexperimental methods for estimating the impact of social programs. *Journal of American Statistical Association, 84*(408), 862-874.

Heckman, J., Ichimura, H., Smith, J. A., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica, 66*(5), 1017-1098.

Heckman, J., Ichimura, H., & Todd, P. (1997). Matching as an econometric evaluation estimator: evidence from evaluating a job training program. *Review of Economic Studies, 64*(4), 605-654.

Heckman, J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *Review of Economic Studies, 65,* 261-294.

Heckman, J., LaLonde, R., & Smith, J. A. (1999). The economics and econometrics of active labor market programs. In A. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 3A, pp. 1865-2089). Amsterdam: Elsevier Science.

Heckman, J., & Robb, R. (1985). Alternative methods for evaluating the impact of interventions: An overview. *Journal of Econometrics, 30*, 239-267.

Heckman, J., & Robb, R. (1986). Alternative methods for solving the problem of selection bias in evaluating the impact of treatments on outcomes. In H. Wainer (Ed.), *Drawing inferences from self-selected samples*. Berlin: Springer Verlag.

Heckman, J., & Vytlacil, E. (1998). Instrumental variables methods for the correlated random coefficient model: Estimating the average rate of return to schooling when the return is correlated with schooling. *Journal of Human Resources, 33*(4), 974-1002.

Heckman, J., & Vytlacil, E. (1999). Local instrumental variables and latent variable models for identifying and bounding treatment effects. *Proceedings of the National Academy of Sciences of the United States of America, 96*(8), 4730-4734.

Heckman, J., & Vytlacil, E. (2000). The relationship between treatment parameters within a latent variable framework. *Economics Letters, 66*, 33-39.

Heckman, J., & Vytlacil, E. (2004). *Structural equations, treatment effects, and econometric policy evaluation*. Working paper. Retrieved January 19, 2005 from http://www.stanford.edu/~vytlacil/_papers/struct_all_2004-12-16_mms.pdf

Hendry, D. (1980). Econometrics: alchemy or science? *Econometrica, 47*, 387-406.

Hershey, A. M., Silverberg, M. K., & Haimson, J. (1999). *Expanding Options for Students: Report to Congress on the National Evaluation of School-to Work Implementation.* (No. EA95010001). Princeton, NJ: Mathematica Policy Research, Inc.

Imbens, G., & Angrist, J. (1994). Identification and estimation of local average treatment effects. *Econometrica, 62*(2), 467-475.

Jarque, C. (1987). An application of LDV models to household expenditure analysis in Mexico. *Journal of Econometrics, 36*, 31-54.

Joyce, M., & Neumark, D. (2001). Evaluating school-to-work programs using the new NLSY. *The Journal of Human Resources, 36*(4), 666-702.

LaLonde, R. (1986). Evaluating the econometric evaluations of training programs with experimental data. *American Economic Review, 76*, 604-620.

Leamer, E. (1983). Let's take the con out of econometrics. *American Economic Review, 73*, 31-43.

Lewis, H. G. (1974). Comments on selectivity biases in wage comparisons. *Journal of Political Economy, 82*, 1145-1155.

Lynch, L. M. (1992). Private-sector training and earnings of young workers. *The American Economic Review, 82*(1), 299-312.

Lynch, L. M. (1993). The economics of youth training in the United States. *The Economic Journal, 103*(420), 1292-1302.

Manski, C. F., & Garfinkel, I. (Eds.). (1992). *Evaluating welfare and training programs*. Cambridge, MA: Harvard University.

Moffitt, R. A. (1999). New Developments in econometric methods for labor market analysis. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor econometrics* (Vol. 3A, pp. 1367-1394). Amsterdam, The Netherlands: Elsevier Science B. V.

Neumark, D. (2002). Youth labor markets in the U.S.: Shopping around vs. staying out. *Review of Economic and Statistics, 84*(3), 462-482.

Neumark, D., & Rothstein, D. (2003). *School-to-career programs and transitions to employment and higher education. NBER working paper 10060.* Cambridge, MA: National Bureau of Economic Research.

Pampel, F. C. (2000). *Logistic regression.* Thousand Oaks, CA: Sage.

Passmore, D. L., Chen, Y., Okou, J., Yu, W., & Lin, C. (2003). *Variation in participation in school-based learning of career skills among U.S. youth.* Paper presented at the 2003 34th annual conference of the Northeastern Educational Association, Kerhonkson, New York.

Pepe, M. S. (2000). Receiver operating characteristic methodology. *Journal of the American Statistical Association, 95,* 308-311.

Quester, A., & Greene, W. H. (1982). Divorce risk and wives' labor supply behavior. *Social Science Quarterly, 63*, 16-27.

Raphael, S., & Stoll, M. (2004). *Evaluating the effectiveness of the Massachusetts Workforce Development System using no-shows as a non-experimental comparison group. Working paper.* Retrieved January 19, 2005 from http://cemmap.ifs.org.uk/docs/cwp1002.pdf

Rosenbaum, P., & Rubin, D. B. (1983). The central role of propensity score in observational studies for causal effects. *Biometrika, 70*, 41-55.

Rosenbaum, P., & Rubin, D. B. (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of American Statistical Association, 79*, 516-524.

Rosenbaum, P., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician, 39*(1), 33-38.

Rothstein, D. (2001a). Youth employment in the United States. *Monthly Labor Review, 124*(8), 6-17.

Rothstein, D. (2001b). Youth employment during school: Results from two longitudinal surveys. *Monthly Labor Review, 124*(8), 25-37.

Rubin, D. B. (1979). Using multivariate matched sampling and regression adjustment to control bias in observational studies. *Journal of American Statistical Association, 74,* 318-329.

Smith, J. A., & Todd, P. (2001). Reconciling conflicting evidence on the performance of propensity-score matching methods. *American Economic Review, 91*(2), 112-118.

Stern, D., Finkelstein, N., Stone, J. R., Latting, J., & Dornsife, C. (1994). *Research on school-to-work transition programs in the United States.* PLACE OF PUBLICATION: National Center for Research in Vocational Education.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica, 26*, 24-36.

Train, K. (1994). *Self-selection bias in a new context: Estimating the impact of conservation programs on measure adoption. Working paper.* Berkeley, CA: U.C. Berkeley.

U.S. Department of Labor, Bureau of Labor Statistics. (2004). The *National Longitudinal Survey of 1997 (Rounds 1-6), 1997-2002 Data Release* [Computer file]. Available from Bureau of Labor Statistics web site, http://www.bls.gov/nls

Wang, B. (1994). Maximum likelihood estimation with sample selection. *Dissertation Abstracts International. A55*(12). (UMI No. 9512792)

Westat. (1981). *Continuous longitudinal manpower survey net impact report no. 1: Impact on 1977 earnings of new FY 1976 CETA enrollees in selected program activities.* (No. 23-24-75-07). Washington, D.C.: U.S. Department of Labor.

Westat. (1984). *Summary of net impact results*. (No. 23-24-75-07). Washington, D.C: U.S. Department of Labor.

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. Cambridge, MA: The MIT Press.

Yu, W., & Passmore, D. L. (2004). Assessing the consequence of school-based learning programs in the United States. Paper presented at the 2004 35th annual conference of the Northeastern Educational Association, Kerhonkson, New York.

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Passmore, D.L., Chen, Y., Okou, J., Yu, W., & Lin, C. (2003). *Variation in participation in school-based learning of career skills among U.S. youth.* Paper presented at the 2003 34th annual conference of the Northeastern Educational Association, Kerhonkson, New York.

Passmore, D. L., Chen, Y., Yu, W., & Lin, C. (2003). *Training, work experience and educational level on wage rates among young people in the United States.* Paper presented at the 2003 34th annual conference of the Northeastern Educational Association, Kerhonkson, New York.

Yu, W., & Passmore, D.L. (2004). *Assessing the consequence of school-based learning programs in the United States.* Paper presented at the 2004 35th annual conference of the Northeastern Educational Association, Kerhonkson, New York.