TWO ESSAYS ON YOUTHS' LABOR SUPPLY

A Dissertation Presented

by

TAO GONG

Submitted to the College of Graduate Studies of the
Middle Tennessee State University in partial fulfillment
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2005

Department of Economics and Finance

APPROVAL PAGE

TWO ESSAYS ON YOUTHS' LABOR SUPPLY

BY

TAO GONG

A DOCTORAL DISSERTATION SUBMITTED
IN PARTIAL FULFILLMENT OF
THE REQUIREMENT FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY / ECONOMICS

MIDDLE TENNESEE STATE UNIVERSITY

~~MAY~~, 2005
AUGUST

APPROVED BY:

Dr. Charles L. Baum II, Committee Co-Chair

Dr. Joachim Zietz, Committee Co-Chair

Dr. Richard L. Hannah, Committee Member

Dr. John T. Lee, Department Chair, Economics & Finance

Dr. Abdul S. Rao, Dean, College of Graduate Studies

APPROVAL PAGE

TWO ESSAYS ON YOUTHS' LABOR SUPPLY

BY

TAO GONG

**A DOCTORAL DISSERTATION SUBMITTED
IN PARTIAL FULFILLMENT OF
THE REQUIREMENT FOR THE DEGREE OF**

DOCTOR OF PHILOSOPHY / ECONOMICS

MIDDLE TENNESEE STATE UNIVERSITY

AUGUST, 2005

ACKNOWLEDGMENTS

I wish to thank Drs. Charles L. Baum II, Joachim Zietz, and Richard L. Hannah for their help, comments, and encouragement. I want to thank Drs. Duane Graddy, Reuben Kyle, Anthon Eff, and Stuart Fowler for their encouragement during my doctoral studies at Middle Tennessee State University. I wish to thank my classmates Xiaolin Zhao, Christian Nsiah, and Assaleenuch Larpcharoen for their help through the first years of graduate school. I thank my parents, Yulong and Jinju, for their financial and emotional support of my studies. I thank my fiancée, Xintao, for being my biggest fan and first reader of my dissertation, and for providing editorial and technical assistance.

ABSTRACT

TWO ESSAYS ON YOUTHS' LABOR SUPPLY

By

Tao Gong

August 2005

Chair: Charles L. Baum II
Co-chair: Joachim Zietz
Major Department: Economics

The first chapter examines the effects of allowances received from family on youths' incentives to work, that is, on hours worked and on the probability of participating in the labor force. The empirical estimates control for unobserved heterogeneity through a number of alternative specifications, including individual fixed effects, sibling fixed effects, and individual differenced sibling fixed effects models. First, across alternative econometric specifications, the results consistently show a negative relationship between allowance and hours worked. The results of simple probit, fixed effects logit, and random effects probit models indicate that a larger allowance reduces youths' probability of participating in the labor force. Marginal effects calculations show that the labor force participation rate of youths with allowance is 11 to 24 percentage points lower than that of youths without allowance. Second, the marginal effect of an allowance on reducing hours worked rises with the amount of the allowance. Third, how hours worked responds to an allowance differs with the education expectation of youths. Youths with high school degrees or GEDs but not enrolled in a college are the most insensitive to a change in the allowance.

The second chapter seeks to analyze the effects of participation in a school-to-work (STW) program on wages of youths in their first job immediately following high school graduation. The empirical method used is a newly developed propensity score estimator. The results show that (1) participation in school-to-work programs has a positive effect ranging from 3.2 percent to 5.8 percent on wages in first primary job immediately following high school graduation; (2) school-based programs are more efficient in increasing the hourly wage than work-based activities because the estimates are not only more significant but also they have larger magnitudes; (3) the effects of particular types of STW programs on wages are not equal. In particular, the coop-education and mentoring activities are the most effective in performing this initiative, which raise wages by 3.8 to 7.7 and 3.9 to 7.7 percentage points per hour, respectively; (4) there is no significant gender difference in the effect of participation in school-to-work programs.

TABLE OF CONTENTS

Page

ACKNOWLEDGMENTS iiv

ABSTRACT v

LIST OF TABLES iix

LIST OF FIGURES xii

CHAPTER

I. ALLOWANCES REDUCE YOUTHS' INCENTIVES TO WORK 1

1 Introduction 1

2 Literature Review 6

3 Theoretical Model 8

4 Empirical Model 13

4.1 Allowances and Hours of Work 13

4.2 Allowances and Labor Force Participation 18

5 Data 20

6 Results 28

6.1 Descriptive Statistics 28

6.2 Empirical Results 35

6.2.1 Effects of Allowance and Covariates on Hours Worked 35

6.2.2 Fixed Effects vs. Random Effects 39

6.2.3 Full Sample vs. Siblings' Sample 41

6.2.4 College-bound Versus Non-college-bound Students 43

6.2.5 Effects of Allowance on the Probability of Labor Force Participation 47

7 Conclusion 52

II. ESTIMATING THE EFFECT OF PARTICIPATION IN SCHOOL-TO-WORK PROGRAMS ON WAGES 55

1 Introduction 55

2 Literature Review 57

3 Theoretical Model 62

4 Data 64

5 Empirical Specification 74

6 Empirical Results 80

6.1 Descriptive Statistics 80

6.2 Regression Results 85

7 Conclusion 97

REFERENCES 99

APPENDIXES 104

LIST OF TABLES

Table Page

Table 1.1: Sample Construction 21

Table 1.2: Descriptive Statistics of Variables 24

Table 1.3: Allowance Received by Annual Hours Worked and By Demographic Characteristics, From 1996 to 2000 29

Table 1.4: Annual Hours Worked by Allowance 31

Table 1.5: Annual Hours Worked by Demographic Characteristics and by Allowance, From 1996 To 2000 33

Table 1.6: Annual Hours Worked by Location Characteristics and by Allowance, From 1996 To 2000 34

Table 1.7: Results of Estimation on Full Sample 35

Table 1.8: Results of Estimation on Siblings' Sample 42

Table 1.9: Results of Estimation by Education Status 46

Table 1.10: Results of Estimation of Probabilities on Full Sample 48

Table 1.11: Results of Estimation of Probabilities on Siblings' Sample 49

Table 1.12: Marginal Effects of Fixed Effects Logit Model 51

Table 2.1: Sample Construction 68

Table 2.2: Descriptive Statistics of Demographic Characteristics and Outcome 72

Table 2.3: School-to-Work Program Participation Rates by Demographic Characteristics 82

Table 2.4: Hourly Rate of Pay by School-to-Work Program and by Demographic Characteristics 84

Table 2.5: Regression Results of OLS 87

Table 2.6: Propensity Score Estimates of the Effect of the participation on Hourly Wage Rate 94

Table 2.7: Propensity Score Estimates of the Effect of the participation on Hourly Wage s By Gender 96

LIST OF FIGURES

Figure — Page

1.1. Simulation of the Impact of Preference Difference on Hours Worked 2

1.2. Labor Force Participation Rate for 16- to 24-year Olds Enrolled in High School, 1993-2002 12

1.3. Annual Allowance Received by Hours and by Gender 30

1.4. Annual Hours Worked by Allowance and By Gender 32

2.1. Histogram of the Estimated Propensity Score for the participation in any School-to-Work Programs 90

2.2. Histogram of the Estimated Propensity Score for the participation in any School-based School-to-Work Programs 90

2.3. Histogram of the Estimated Propensity Score for the participation in any Work-based School-to-Work Programs 91

Chapter I

Allowances Reduce Youths' Incentives to Work

1. Introduction

There is a high rate of labor force participation among high school students. According to the Bureau of Labor Statistics, 37.0 and 34.7 percent of high school students were either employed or looking for work in October 2001 and 2002, respectively (Figure 1.1). That translates to more than 3 million high school students participating in the labor force. What causes so many youths to work part-time while enrolled in school? Do youths work for money to pay for personal expenses, to help their families, or for job experience? Early employment experiences of youths could provide students opportunities to learn vocational skills and knowledge that they need to be successful in the world of work and consolidate what they have learned in school.[1] Therefore, their employment could signal to employers that they have acquired the necessary technical skills for a faster and more successful transition from school to work. This belief is especially important for those that are not bound for college because they have less education than those that have college degrees.

Greenberger and Steinberg (1986) find in their study of employed high school students that the chief reason for working is to make money rather than to achieve work experience or skills. Their study indicates that 38 percent of the employed high school students in the sample work "in order to earn money for things [they] really needed," and 36 percent of them claimed that "[they] didn't really have to work, but [they] want to

[1] Evidence suggests that early work experience is beneficial to future labor market outcomes. See Carr, Wright, and Brody, 1996; Ruhm, 1997; Mortimer and Joshdon, 1998; Ghosh, 1999.

have money for 'extras' " (Greenberger & Steinberg, 1986). An earlier national survey of more than 18,000 high school seniors in 1981 concludes that most spend at least half or all of their earnings on personal needs (Johnston, Bachman, & O'Malley, 1982) rather than supporting their families. A recent report indicates that two-fifths of high school seniors spend most of their earnings on personal items (U.S. Department of Education, 1996). More than 80 percent replied that "none or only a little" of their earnings were to help families meet financial expenses. Yeatts (1994) reports that 69 percent of employed high school seniors indicate that some of their earnings go toward car expenses, 97% of them spend their earnings on "buy[ing] things", and just 44% of the employed senior students work to save for college.

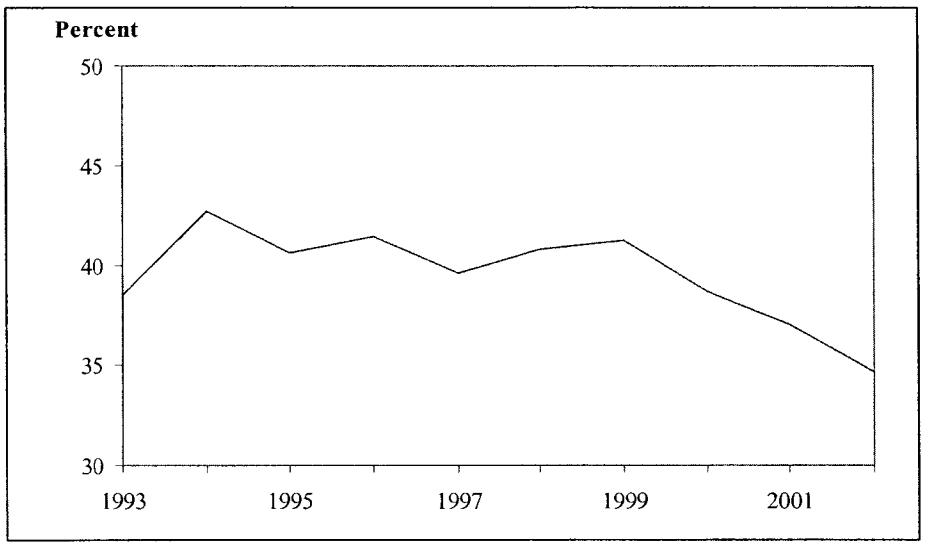

FIGURE 1.1 LABOR FORCE PARTICIPATION RATE FOR 16- TO 24-YEAR OLDS ENROLLED IN HIGH SCHOOL, 1993-2002

Thus, it is apparent that the primary motivation for youths to work is to finance short-term personal consumption rather than to support family expenses or to save for college. One major reason behind this motivation is the increasing interest in acquiring material goods that has been observed over the last few decades (Greenberger and Steinberg, 1986; Marsh, 1991; and Lewis, 1999). Today's youths want not only expensive clothes and entertainment but also have more needs such as cell phones, computers, and cars than yesteryear's (Brazil, 1999). Parents do not always support these expensive needs of their children; therefore, the children have to work. The rising real cost of consumer goods of interest to teenagers has exacerbated this trend. In 1994, the national average price for a movie ticket was $4.08 and for a gallon of unleaded regular gasoline was $1.16.[2] By 2001, the corresponding costs have inflated to $5.65 and $1.34, respectively.[3] That is, the same items cost 19 percent and 16 percent more in 2001 than in 1994, respectively. Therefore, if allowance cannot keep up with the higher material expectations and inflation or if there is little or no allowance, youths have to go to work to supplement their income. The work-leisure model asserts that, with a constant opportunity cost of leisure and for a constant wage rate, a higher allowance means a person would consume more leisure and work less. That is, if allowances are increased, youths will reduce their willingness to participate in the labor market. However, there is very little empirical evidence on this topic (U. S. Department of Labor, 2000). The purpose of this paper is to fill this gap in the literature. To that end, the paper uses a new data set, the National

[2] Dorfman (1982) provides an example to show the inflation on some of the traditional goods purchased by teenagers. He compared the prices of a movie ticket and a gallon of gasoline in 1967 with the prices of these two goods in 1982.

[3] The price of a movie ticket in 2000 is from http://www.natoonline.org/statisticstickets.htm and it is not adjusted for inflation. The price of a gallon of gasoline in 2000 is in real dollars and it is from http://www.eia.doe.gov/emeu/aer/pdf/pages/sec5_51.pdf.

Longitudinal Survey of Youth 1997 (NLSY97). For this data set, it will examine the relationship between allowance and youths' labor participation behavior.

The following questions will be addressed to determine whether youths' participation in the labor force is affected by allowances:

(1) Is there a negative relationship between allowance and hours worked? That is, does a larger allowance reduce youths' incentives to work? If this is the case, then the motivation of youths to work is affected by allowances. Such a finding would suggest that the work-leisure model applies and the primary reason for youths to seek paying jobs is money.

(2) If a larger allowance reduces the number of hours worked, is the magnitude of reduction in hours worked proportional to the base level of the allowance? That is, does a given increase in the allowance reduce a youth's hours worked more if the increase applies to a higher than to a lower base level of the allowance? It is expected that such a proportional effect exists because a given dollar increase has less of an impact at a lower allowance level than at a higher allowance level.

(3) If a negative relationship exists between allowance and hours worked, does a larger allowance reduce hours worked equally for different groups of youths? Do youths with different career objectives respond the same? In this case it would appear that youths participate in the labor force primarily for money, not for the value of the working experience. One part of this study focuses exclusively on youths that are not bound for college or are without high school degrees or GEDs. The effect of a change in allowance on hours worked may be smaller for them

because their main motivation to work while in high school may be to obtain job experience and, thereby, to ease their transition from school to work. If they behave systematically different from those bound for college, then examining this sub-sample will reduce potential bias from unobserved heterogeneity.

This chapter will provide empirical evidence on the relationship between teenagers' allowance and hours of work and the probability of participating in the labor force. The findings and conclusions will be useful to policy makers, educational planners, and program developers. It could also benefit School-to-Work program implementation, development, and legislation regarding minimum wages and driver's licensing (Pabilonia, 2001). For example, if most youths have no need to support family or pay for household expenses, then they can afford to work at or even below minimum wage. Previous research has shown that most adolescents are not as concerned with relatively low wages, as are adults (Greenberger & Steinberg, 1986). In this regard, a lower minimum wage for youths could be proposed in order to create more job opportunities. Therefore, the results would have important implications for minimum wage legislation.

The chapter is organized as follows: section 2 reviews the literature; section 3 develops the theoretical model; sections 4 and 5 outline the empirical modeling and describe the data and sample selection process; section 6 presents the empirical results; and section 7 concludes the chapter.

2. Literature Review

How allowances affect youths' employment behavior remains an unsettled issue. One of the main reasons is the inadequate empirical evidence. Until very recently, no large representative data set has been available with well-measured information on allowances.

Dustmann and Micklewright (2001) analyze the relationship between intra-household transfers and children's labor supply, cash transfers, and weekly hours of work. They develop a theoretical model based on the Rotten Kid Theorem to examine the labor force participation of British sixteen-year-old children. By applying a simultaneous equations approach, they find that participation in the labor force negatively affects parental transfers, which in turn reduces the hours worked and the probabilities of labor force participation of youths.

Pabilonia (2001) uses the first round NLSY97 data to study the association between parental allowances and youth employment (annual hours worked and earned income) for dependent youths. Employing a probit model, she finds that the probability of earning income is negatively affected by allowance although the magnitude is quite small. Estimating a tobit model, she also finds that earnings from working at freelance-, self-employment-, and employee-types of jobs are negatively affected by parental transfers for youths ages 14 through 16.

In a related study, Goldfarb and Yezer (1983) develop a theoretical model of youth labor supply that maximizes teenager utility. In a simultaneous equations framework, they examine market level (Statistical Metropolitan Survey Area) data on average

teenagers' wages and annual weeks worked by youths aged 16-20. They disaggregate the data by family type, age, and gender, which allows them to study teenagers subject to different family constraints. They conclude that the effect of non-labor income on hours of market work is not significant.

The existing studies suffer from some common shortcomings. First, the literature uses cross-sectional rather than longitudinal data and is, therefore, only able to determine the effects of allowances at a particular point in time. Second, the use of cross-sectional data does not allow one to control for unobserved characteristics of individuals that might be correlated with allowances and other outcomes. Third, the literature's results appear to be sensitive to slight changes in the particular specification of the estimating equation or research methodology. For instance, in Dustmann and Micklewright (2001), the coefficient of parental transfers on hours worked is significant in the simultaneous equations framework but insignificant when tested with alternative model specifications. Sensitivity to model specification also exists in the related studies on the relationship between non-wage income and hours worked. Pencavel (1986) indicates that different measurements of non-wage income result in both a negative as well as a positive association between non-wage income and hours of work.

This study will contribute to the literature in several ways. First, this study develops a youth labor supply model that incorporates both current and future consumption based on utility maximization. Second, because a panel data set is used, it is possible to control for the unobserved heterogeneity that is correlated with allowances. Unbiased estimates are obtained through a number of fixed- and random-effects estimators. Third, disaggregation

of teenage groups by education expectations makes it possible to explore whether money or job experience is the primary motivation for youths to work. Fourth, the empirical robustness of parameter estimates will be assessed by comparing the results from both fixed- and random-effects estimators and from different model specifications. Finally, by shedding new light on the relationship between allowances and hours of work of teenagers new empirical evidence will be provided for the work-leisure model.

3. Theoretical Model

The following labor supply model is developed to provide guidance in specifying the empirical framework. Following Dustmann and Micklewright (2001), an individual is assumed to have preferences defined over three commodities: current consumption, C_1, future consumption, C_2, and leisure (time outside the labor market), L. It is also assumed that the preferences can be expressed by a utility function $U = U(C_1, C_2, L)$ where $U'>0$ and $U''<0$. Consider the utility maximization problem:

$$(1) \qquad \underset{C_1,C_2,L}{Max}\, U(C_1, C_2, L) \cdot$$

Assume that youths face a wage or an opportunity cost of leisure per unit of time in the labor market, w, and an allowance received from parents (non-labor income), F. The decision variables in (1) are subject to the budget constraint,

$$(2) \qquad C_1 = wT_w + F,$$

where T_w is the time spent on market work. Normalizing the total time available for school, T_e, work, and leisure activities to 1, the utility maximization decision is also subject to the time constraint,

(3) $1 = T_w + T_e + L$.

Future consumption, C_2, depends on productivity, which is determined by human capital accumulated through education or work experience accumulated as a youth and is given by

(4) $C_2 = \theta H$

where H is the stock of human capital and θ is a factor of labor productivity. H is a concave human capital production function that depends on the amount of time spent in school, T_e, the amount of time worked, T_w, and an unobserved mental ability or motivation, A, where $H'>0$ and $H''<0$; therefore,

(5) $H = H(A, T_e, T_w) = \alpha A + \beta T_e + \gamma T_w$.

For simplicity, assume that the utility function is of the constant return Cobb-Douglas form,

(6) $U = C_1^{a_1} C_2^{a_2} L^{a_3}$

where $a_1 + a_2 + a_3 = 1$. Substituting (2), (3), (4), and (5) into (6) gives

(7) $U(C_1, C_2, L) = (wT_w + A)^{a_1} (\theta(\alpha A + \beta T_e + \gamma T_w))^{a_2} (1 - T_w - T_e)^{a_3}$

Assuming an interior solution, the first order condition of utility maximization of (7) with respect to T_w yields:

$$\frac{\partial U}{\partial T_w} = \frac{a_1 w(wT_w + A)^{a_1}(\theta(\alpha A + \beta T_e + \gamma T_w))^{a_2}(1 - T_e - T_w)^{a_3}}{wT_w + A}$$
$$+ \frac{a_2 \gamma (wT_w + A)^{a_1}(\theta(\alpha + \beta T_e + \gamma T_w))^{a_2}(1 - T_e - T_w)^{a_3}}{\alpha A + \beta T_e + \gamma T_w}$$
$$- \frac{a_3 (wT_w + A)^{a_1}(\theta(\alpha A + \beta T_e + \gamma T_w))^{a_2}(1 - T_e - T_w)^{a_3}}{1 - T_e - T_w} = 0$$

The second order conditions are satisfied if the utility function is strictly concave. The optimal amount of labor supply, T_w, given the allowance or non-labor income, is as follows:

$$(8) \qquad T_w = \begin{cases} \dfrac{a_1(\alpha A + \beta)}{\beta - \gamma} - \dfrac{(a_2 + a_3)F}{w} & \text{for } 0 \le F < \dfrac{a_1 w(\alpha A + \beta)}{(a_2 + a_3)(\beta - \gamma)} \\ 0 & \text{for } F \ge \dfrac{a_1 w(\alpha A + \beta)}{(a_2 + a_3)(\beta - \gamma)} \end{cases}$$

There are several fundamental features implied in the model. First, youths will not participate in the labor force as long as the allowance exceeds $\frac{a_1 w(\alpha A + \beta)}{(a_2 + a_3)(\beta - \gamma)}$. The threshold depends on the wage rate, w, the youth's preferences for time spent on school and work, β and γ, and the unobserved mental ability, A. That is, higher wages increase youths' incentives to supply labor, which implies that an allowance deters youths from entering the labor market.

Second, for the preference between school and work, β and γ, if youths believe that school plays a more important role than work experience in the accumulation of human capital, then the coefficient of time spent on school, β, will be greater than that on work, γ. Both $\beta > 0$ and $\gamma > 0$ is assumed, which means that both school and work are beneficial to the accumulation of human capital. The smaller the difference $|\beta - \gamma|$, the larger needs to be the allowance to discourage youths from participating in the labor force. If teenagers believe that work is detrimental to the accumulation of human capital, then γ will be negative. If the difference $|\beta - \gamma|$ is larger, a lower allowance is needed to deter youths from working. To summarize, if youths believe that time worked has a positive effect on human capital accumulation, then they are likely to work more hours even if they have a sufficient allowance. Therefore, time worked depends on youths' attitudes about work, which to a large extent is influenced by their parents (Goldfarb and Yezer, 1983). In this regard, the traditional negative effect of non-labor income on labor supply cannot be assumed without considering the characteristics of youths and their family background because more non-labor income (allowance) does not necessarily imply fewer hours worked. Figure 1.2 simulates a negative impact of the difference $|\beta - \gamma|$ on hours worked.

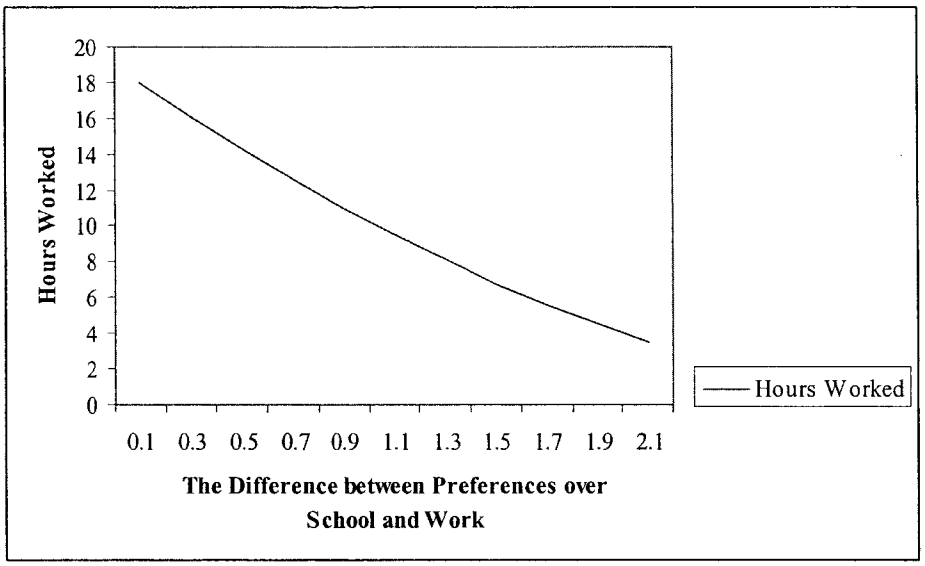

FIGURE 1.2 SIMULATION OF THE IMPACT OF PREFERENCE DIFFERENCE ON HOURS WORKED

Third, if the allowance is less than $\frac{a_1 w(\alpha A+\beta)}{(a_2+a_3)(\beta-\gamma)}$, then youths will work $\frac{(\alpha A+\beta)}{(\beta-\gamma)}-\frac{(a_2+a_3)F}{w}$ hours. The sum (a_2+a_3) also affects the number of hours worked by youths. The parameters a_2 and a_3 are the elasticities of utility with respect to future consumption and current leisure, respectively. If (a_2+a_3) is positive, then hours worked will be decreasing in allowance. However, if (a_2+a_3) is negative, then hours worked will be increasing in allowance. This finding is contradictory to theory because the work-leisure model asserts that, if non-labor income increases, then hours worked will decrease. Therefore, the role of an allowance is similar to that of the real wage rate in the decision between work and leisure. If the number of hours worked increases with the allowance, then the income effect plays a more important role than the substitution effect, and vice versa.

4. Empirical Model

The empirical analysis consists of two parts. The first part examines to what extent allowances received from parents affect youths' hours of work. The econometric analysis of this first part relies on five econometric methods: ordinary least squares (OLS), an individual-specific fixed effects model, a sibling fixed effects model, an individual differenced-sibling fixed effects model, and a random effects model. The second part investigates whether allowances have an impact on the probability of labor force participation. The econometric modeling for this second part makes use of a maximum likelihood probit model, a fixed effects logit model, and a random effects probit model that can correct for unobserved heterogeneity.

4.1 Allowances and Hours of Work

The hours worked regression equation is specified as

$$(1) \qquad T_{it} = \beta X_{it} + \varepsilon_{it}$$

where T is hours worked, X is a series of exogenous variables that includes any allowance received from parents, i and t index person and year, and ϵ_{ij} is a random error term with the assumptions of E (ϵ_{ij}) = 0 and Cov (x_{ij}, ϵ_{ij}) = 0. This model is estimated by OLS regression.

If there are unobserved factors that are correlated with the explanatory variables in X, such as cognitive ability, motivation, or level of lifetime utility (Kaestner, 1992), and that affect hours of work, the coefficients estimated by OLS will be biased due to unobserved

heterogeneity. For instance, a youth who has good academic performance in school is likely to be rewarded by parents with an allowance (Miller and Yung, 1990).[4] If good performance is related to the youth's ability or motivation, then these unobserved variables are correlated with the key independent variable allowance. Likewise, youths with higher ability and motivation are more capable of working more hours while performing well in school. Hence, these unobserved effects are also correlated with the dependent variable, T_{ij}. Therefore, the error term is not random, and estimation by OLS will produce biased estimates. The first approach to avoid such bias is to use an unusually large number of covariates to control for individual-specific unobserved factors in the error term that are potentially correlated with X_{ij} and that might affect hours of work.

The second approach is to re-estimate specification (1) allowing for an individual fixed component, c_i, to be correlated with X and constant over time. Thus, the estimating model becomes

(2a) $T_{it} = \beta X_{it} + c_i + \epsilon_{it.}$

With panel data, one can difference (2a) across two adjacent time periods to eliminate the time-constant unobserved heterogeneity, c_i

(2b) $(T_{it} - T_{it-1}) = (\beta X_{it} - \beta X_{it-1}) + (c_i - c_i) + (\epsilon_{it} - \epsilon_{it-1})$.

If one defines

$\Delta T = T_{it} - T_{it-1}$, $\Delta X = X_{it} - X_{it-1}$, and $\Delta \epsilon = \epsilon_{it} - \epsilon_{it-1}$,

[4] Miller and Yung (1990) find that 2.8 percent of public high school students in New York City in 1988 indicate that achievement is one of the most important reasons for allowance.

where X is a vector of explanatory variables that includes the allowance variable, the estimating model can be written in first differenced form as

$$\Delta T = \Delta X\beta + \Delta\epsilon,$$

which is just a standard linear model of the differences of all variables. OLS can be applied to this equation and it will yield unbiased estimates assuming the unobserved heterogeneity is fixed over time. This approach is commonly used in the literature (Korenman and Neumark, 1992; Ashenfelter and Zimmerman, 1993; and Waldfogel, 1997).

The third model includes a family fixed component, c_f, which represents family-specific unobserved heterogeneity. The family component is intended to eliminate estimation bias that would arise from unobserved attitudes of parents toward their children working while in school. For example, if parents were benefited from their early work experience, then they may have positive attitudes towards their children's working. Otherwise, parents may try to deter their children from working by all means such as increasing their allowance. Therefore, such behavior would cause the unobserved attitudes of parents to be correlated with the variables allowance and hours worked. Such a problem can be solved by using the family fixed effects models, which can be written as

$$(3a) \quad T_{it} = \beta X_{it} + c_f + \epsilon_{it},$$

where f indexes families. The component c_f is fixed at time t but changes across family f. The family fixed effects model can remove the problem of unobserved heterogeneity

because it assumes the unobserved factors are identical to all members in the same family. Therefore, the unobserved family fixed effect can be differenced out by using the sample of siblings that includes at least two respondents in one family. Though the unobserved heterogeneity is not constant over time, equation (3a) can be differenced across siblings in the same family to eliminate the family-constant unobservable, c_f. This approach is used in the literature, for example, by Lunderberg and Rose (2001) and Baum and Ford (2004) to generate OLS estimates that are unbiased. The absence of bias is conditional on the assumption that the unobserved variables are constant across siblings. Such an assumption would, for example, be violated if parents treated their male children differently from their female ones. In differenced form, equation (3a) can be written as

(3b) $T_{it} - T_{jt} = \beta (X_{it} - X_{jt}) + (\epsilon_{it} - \epsilon_{jt})$.

The fourth approach to deal with unobserved heterogeneity is to allow for both c_i and c_f to be correlated with the X_{it}. In the presence of time-constant individual fixed effects and family-constant fixed effects, the model is given as

(4a) $T_{it} = \beta X_{it} + c_i + c_f + \epsilon_{it}$.

Assuming that at least two time periods and siblings are available, (4a) can be differenced across both time periods and siblings,

(4b) $(T_{it} - T_{it-1}) - (T_{jt} - T_{jt-1}) = [\beta (X_{it} - X_{it-1}) + (c_{it} - c_{it-1}) + (c_{ift} - c_{ift-1}) + (\epsilon_{it} - \epsilon_{it-1})] - [\beta (X_{jt} - X_{jt-1}) + (c_{jt} - c_{jt-1}) + (c_{jft} - c_{jft-1}) + (\epsilon_{jt} - \epsilon_{jt-1})]$.

Since $c_{it} = c_{it-1}$, $c_{ift} = c_{jft}$, $c_{jt} = c_{jt-1}$, and $c_{ift-1} = c_{jft-1}$, the postulated unobserved effects c_i and c_f cancel out in (4b) and unbiased coefficient estimates result.

The last alternative solution to the unobserved heterogeneity problem is the estimation of a random effects model. Although fixed effects models can produce consistent and unbiased coefficients in the presence of time-invariant unobserved variables, this modeling approach has the disadvantage that one loses time-invariant observable variables from the regression. Time-constant observables simply cannot be distinguished from time-constant unobservables (Woolbridge, 2001). A random effects model eliminates these problems because it is capable of identifying the effects of time-constant observable variables, such as gender and race. As Wooldridge (2001) suggests, c_i is put into the error term and equation (2b) is re-written as

(5a) $T_{it} = \beta X_{it} + v_{it}$

where $v_{it} = c_i + \epsilon_{it}$ is the composite error, which consists of the sum of the unobserved effect and an idiosyncratic error. Under the assumptions that the term c_i is orthogonal to X_{it}, $E(c_i|X_i) = E(c_i) = 0$, and that strict exogeneity exists between the explanatory variables and the composite error, $E(v_i|X_i) = 0$, the random effects model can be consistently estimated by generalized least squares (GLS) (Wooldridge, 2001). However, orthogonality between the unobserved effect and the regressors is a strong assumption. If it is not true, then GLS will be severely biased due to the correlation between the unobserved factors and the explanatory variables. Therefore, Hausman's (1978) specification test is used to check whether the random effects estimator is consistent and efficient. If the test statistic is not significant at the 10 percent level, the orthogonality

assumption holds and the coefficients of the random effects estimator are reported because it is a more efficient estimator that provides better p-values than the fixed effects estimators.

4.2 Allowances and Labor Force Participation

The models discussed in the previous section are intended to examine the impact of various characteristics of youths on their hours worked. To explain the effects of X_{it} on the probability of being employed, regardless of the number of hours worked, a probit model is estimated,

$$(6) \qquad P(T_{it} = 1 | X_{it}) = G(\beta X_{it}),$$

where $G(.)$ is the standard normal cumulative distribution function, X_{it} is a series of exogenous variables, and where i and t index individuals and periods, respectively.

To control for unobserved effects, a random effects probit model and a fixed effects logit model are used. The former can be expressed as

$$(7) \qquad P(T_{it} = 1 | X_{it}, c_i) = \Phi(\beta X_{it} + c_i)$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function (cdf). For the fixed effects logit model, the standard normal cdf $\Phi(\cdot)$ in (3) is replaced by the logistic function $\Lambda(\cdot)$, where $\Lambda(X_{it}\beta + c_i) = \frac{e^{X_{it}\beta + c_i}}{1 + e^{X_{it}\beta + c_i}}$.

The fixed effects probit model is not used because it suffers from the incidental parameters problem (Neyman and Scott, 1948 and Lancaster, 2000). As discussed in Wooldridge (2001), as N goes to infinity and t is fixed, the number of fixed effects, c_i, increases with N, which means that they cannot be consistently estimated given a fixed T. A fixed effects (conditional) logit model is used to tackle this problem. In the logit model, the conditional distribution does not depend on the individual effects.

The coefficients in non-linear models are difficult to interpret because they only provide the direction but not the magnitude of the marginal effect of a variable on the estimated probabilities. Thus, to cope with this problem, the coefficients of continuous variables need to be rescaled to obtain marginal effects. For the normal distribution, the marginal effect is calculated as follows,

$$(8) \qquad \frac{\partial P(T_{it}|X_{it},c_i)}{\partial X} = \Phi(\beta X_{it} + c_i)\beta$$

where $\Phi(\cdot)$ is the standard normal density function. For the logistic distribution, the marginal effect is

$$(9) \qquad \frac{\partial P(T_{it}|X_{it},c)}{\partial X} = \gamma(X_{it}\beta + c_i) = \Lambda(X_{it}\beta + c_i)(1 - \Lambda(X_{it}\beta + c_i))$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function.

The marginal effect for a binary independent variable is the discrete change from 0 to 1 of the dummy. Thus, the marginal effect is

$$(10) \quad \Pr[Y=1|\overline{X}_{(d)}, d=1] - \Pr[Y=1|\overline{X}_{(d)}, d=0]$$

where d is a binary independent variable and $\overline{X}_{(d)}$ denotes the means of all the other variables in the model.[5]

5. Data

The data come from the National Longitudinal Survey of Youth 1997 (NLSY97). The data set contains extensive information on youths' labor market experience, including annual hours worked, and information on youths' income, such as annual allowance. The NLSY97 is a nationally representative sample of 8,984 youths (4,385 of whom are female) who were between the ages of 12 and 16 years old as of December 31, 1996. Youths come from 6,819 unique households and, among them, 1,862 have more than one respondent in the cohort. The first interview of the survey took place in January 1997 and subsequent interviews have been conducted on an annual basis since then. Both the eligible youths and their parents received hour-long personal interviews. The cohort consists of two sub-samples: (1) a cross-sectional sample of 6,748 respondents and (2) a supplemental sample of 2,236 Hispanic and African-American young people (NLSY97 User's Guide, 2002). The NLSY97 original sample is weighted to be nationally representative.[6] This paper makes use of the first five rounds of data available to the public, which covers 1996 through 2000. Table 1.1 presents the sample used and describes the process of sample construction. Row (1) of the table reports the overall sample includes 44,590 person-year observations.

---

[5] Detail is in Chapter 21, Econometric Analysis, Greene, William H. 2003.
[6] In this paper, the sample is not weighted. See Baum 2003.

TABLE 1.1 SAMPLE CONSTRUCTION

	Number of Observations
(1) Total observations	44920
Condition on restriction variables	
(2) (1) with valid answer for marry question	41522
(3) (2) with valid answer for enroll question	41394
(4) (3) with valid answer for child question	41345
Condition on key variable	
(5) (4) with valid answer for allowance question	40536
(6) (5) replaces allowance > $2,000 with $2,000	40536
Condition on outcome variable	
(7) (6) with valid answer for hours worked	37103
Condition on explanatory variables	
(8) (7) with valid answer for Grade question	36616
(9) (8) with valid answer for Height in foot	36326
(10) (9) with Valid answer for ASVAB score	36185
(11) (10) with valid answer for household gross income question	36185
(12) (11) replaces household gross income < 0 with 0	36185
(13) (12) with valid answer for Household relationship question	36054
(14) (13) with valid answer for Number of children under 18 question	35803
(15) (14) with valid answer for Number of children under 6 question	35803
(16) (15) with valid answer for Region question	35707
(17) (16) with valid answer for MSA	35666
(18) Dependent youths	22506
(19) Independent youths	13160
(20) (9) deletes invalid answer for household gross income question	*31322*
(21) (20) deletes household gross income < 0	*31319*
(22) deletes allowance > $2,000	*31033*
(23) Dependent youths	*20665*
(24) Independent youths	*10368*

Notes: There are 22,506 person-year observations in the sample. Valid answer means no 'invalid skipping', no 'I do not know', and no 'refuse to answer'. Italic numbers means an alternative way of sample construction.

The sample presented in Table 1.1 is disaggregated it into two subgroups, dependent and independent youths. Independent youths refer to respondents who "are age 18 or older, have had a child, are enrolled in a 4-year college, have ever been married or in a marriage-like relationship at the time of the survey, are no longer enrolled in school, or

are not living with any parents or parent-figures" (NLSY97 User's Guide 2002, 214).[7] The main question of interest in this study is the employment behavior of dependent youths because their behavior is more likely affected by an allowance received from family. The amount of the allowance is very possibly affected by the independent status of youths. That is, if youths choose to be independent, then they are more likely to work. As a result, their allowance is more likely to be reduced and may not truly be exogenous. Furthermore, some questions are only applicable to independent youths because their relationships with their parents may be different from that of dependent youths. For example, only independent youths were asked whether their parents give any money, including any gifts, in the form of cash or a check. This is probably due to the fact that the independent status has changed their relationships with their parents and the allowance is not necessarily a principle source of income, and they do not expect much from family. For these reasons, independent youths are dropped out of this study and only dependent youths are included. Dependent youths are restricted to meet all characteristics, which require them to be younger than age 18, to have no children, to be not enrolled in a 4-year college, to be not married or in a marriage-like relationship at the time of the survey, and to be enrolled in school. However, the family status of youths, (living with parents or apart) is not required because this information is not available in all rounds. As reported in Rows (2)-(4) in Table 1.1, only a few observations were lost because of these restrictions.

All dependent respondents reported whether they received an allowance from their family during the previous year and how much they received. As indicated in Row (5),

[7] The definition is from NLSY97 User's Guide 2002, p. 214.

invalid answers for this question are deleted and observations from answers that were skipped for a valid reason are replaced with zero. Answers that were skipped for a valid reason come from youths that did not receive any allowance from their family during the previous year, and invalidly skipped answers are from youths that received allowances from their parents during the previous year but did not show how much they received.[8] All allowance data are deflated using the Consumer Price Index (1997 = 100). The average allowance for the dependent youths sample is about $159.16 per year (Table 1.2).

The NLSY97 classifies jobs into four types: employee-type jobs, freelance-jobs, self-employment, and military service. Employee-type jobs are defined as where the respondent has an ongoing relationship with a specific employer (NLSY97 User's Guide, 2002).[9] A series of questions about employee jobs are answered by youths age 14 and older. Freelance-type jobs refer to jobs for which the respondent performed one or a few tasks for several people without a specific boss, or in which the respondent worked for him- or herself, such as with baby sitting and snow shoveling.[10] Respondents aged 16 or older, who usually earn $200 or more per week at a freelance job, are considered self-employed. Additional information was collected about those jobs as part of the freelance section of the survey. Respondents aged 14 and over with employee jobs and all respondents aged 12 and 13 with freelance jobs provide information about the number of hours worked during the year. Total annual hours worked at all jobs including freelance, self-employment, and employee types are taken to be the dependent variable in this study because it is available for all rounds. Labor force participation is defined as having

[8] Invalid skip includes "refusal", "I do not know", and "invalid skip".
[9] The definition is from NLSY97 User's Guide 2002, p. 96.
[10] The definition is from NLSY97 User's Guide 2002, p. 96.

TABLE 1.2 DESCRIPTIVE STATISTICS OF VARIABLES

Variable	Dependent Youths		Full Sample	
	Mean	Std. Dev	Mean	Std. Dev
Dependent variable:				
Hours of work per year	149.11	339.96	375.48	620.62
Participate in labor force (=1 if in labor force)	0.32	0.47	0.49	0.50
Explanatory variables:				
Allowance(1000s)	0.16	0.32	0.14	0.33
Low allowance (=1 if (0,260))	0.23	0.42	0.17	0.38
Mid Allowance (=1 if [260,520))	0.11	0.31	0.08	0.28
High allowance (=1 if [520,2000])	0.08	0.27	0.07	0.26
Personal Characteristics				
Age (in years)	14.84	1.41	15.93	1.99
Gender (=1 if male)	0.52	0.50	0.50	0.50
Black (=1 if black)	0.25	0.43	0.25	0.43
NBNH (=1 if non-black and non-Hispanic)	0.54	0.50	0.53	0.50
Hispanic (=1 if Hispanic)	0.20	0.40	0.21	0.41
Grade (GPA in 8th grade)	5.64	1.66	5.64	1.66
Height (in inches)	66.28	4.24	66.63	4.22
AFQT	0.00	1.00	0.08	1.01
Family Characteristics				
No household income (=1 if 0)	0.67	0.47	0.46	0.50
Low household income (=1 if (0,25,000))	0.76	0.43	0.60	0.49
Middle household income (=1 if [25,000,50,000))	0.15	0.35	0.23	0.42
High household income (=1 if [50,000,75,000))	0.05	0.22	0.07	0.26
Mother complete high school (=1 if complete)	0.30	0.46	0.30	0.46
Mother complete college (=1 if complete)	0.15	0.36	0.15	0.35
Father complete high school (=1 if complete)	0.24	0.43	0.23	0.42
Father complete college (=1 if complete)	0.17	0.37	0.16	0.37
Both parents (=1 if has both parents)	0.65	0.48	0.58	0.49
Single parent (=1 if has single parent)	0.29	0.46	0.28	0.45
Number of siblings between age 6 and 18	1.97	1.13	1.55	1.25
Number of siblings under age 6	0.16	0.45	0.21	0.53
Mother has income (=1 if mother has income)	0.70	0.46	0.74	0.44
Father has income (=1 if father has income)	0.63	0.48	0.67	0.47
Location Characteristics				
South (=1 if lived in south)	0.37	0.48	0.38	0.48
North-east (=1 if lived in north-east)	0.17	0.38	0.17	0.38
West (=1 if lived in west)	0.23	0.42	0.22	0.42
MSA (=1 if in Metropolitan Survey Area)	0.81	0.39	0.82	0.39
County unemployment rate	34.49	28.49	37.76	26.46

Notes: Base category for *allowance* is equal to $0; base category for *parents' income* is more than $75,000; base category for *region* is North-central; base category for *parents' education* is <= 8th grade including no education; base category for *race* is mixed race/ethic; base category for *the relationship to parents* is no parents; base category for *MSA* is lived in urban. Full sample includes both dependent and independent youths.

worked for pay during the previous year. As reported in Row (7), invalid data including 'refusals' and 'I do not know' on hours worked are deleted and, likewise, validly skipped answers which refer to youths that did not work at all during the past year are replaced with zero.

In addition to the variables of interest, several groups of covariates are included to control for pre-employment differences. The first group of covariates relate to demographic characteristics of respondents. Previous studies have identified significant effects of gender, age, race, and ethnicity on youths' labor supply (Pabilonia, 2001 and Huang et. al., 2001).[11] All respondents are identified as Hispanic, black, non-black/non-Hispanic, or mixed race/non-Hispanic. Other variables employed in the study include the grade marks received in 8th grade, measured on an eight point scale, and height in inches. Grades received range from "mostly Ds" to "mostly As". The categories "As to Cs", "mixed", "ungraded", "skipped 8th grade", and "other" are replaced with the sample mean.[12] Youth's height is used to control for their physical conditions and is useful in predicting youths' employment behavior (Pabilonia, 2001 and Dustmann and Micklewright, 2001). Respondents that refused, did not know, and invalidly skipped the question "approximately what is your height in feet" are dropped from the sample. For those that answer this question but refuse, do not know, and invalidly skip the question "approximately what is your height in inches" missing inches are imputed to the midpoint 6. As Rows (8) and (9) indicate, adding this group of variables does not reduce the sample size substantially.

---

[11] Pabilonia (2001) finds that age affects youths' labor market participation positively.

[12] Grades received in 8th grade include mostly below Ds = 1, mostly Ds = 2, about half Cs and half Ds = 3, mostly Cs = 4, about half Bs and half Cs = 5, mostly Bs = 6, mostly about half As and Bs = 7, As = 8, As to Cs = 9, mixed = 10, ungraded = 11, skipped 8th grade = 12, and other = 13.

The AFQT (Armed Forces Qualification Test) score is employed to control for the impact of unobserved ability and aptitude on youths' hours worked. The AFQT is not only a good measure of the likelihood that enlistees are successful in the military, but it is also a good predictor of initial success in the civilian labor force (NLSY97 User's Guide, 2002). However, it has not been available from the NLSY97 so far. Fortunately, the AFQT is a combination of four subtests' scores of the Armed Services Vocational Aptitude Battery (ASVAB). During round 1, there are 7,127 out of 8,984 respondents that completed this test. In particular, 80.8 percent are from the cross-sectional sample and 74.9 percent from the oversample (NLSY97 codebook supplement, appendix 10). For the respondents that did not take the ASVAB tests, the missing values are replaced with the sample means. Invalid responses are deleted from the sample, as indicated in Row (10) of Table 1.1. The ability estimates for each subtest may have positive or negative values. Youths with positive scores have above average abilities compared to those with negative scores. The AFQT score can be obtained as the sum of the scores of the mathematical knowledge and arithmetic reasoning subtests plus two times the subtests' scores of word knowledge and paragraph comprehension.[13] To interpret the coefficient of the AFQT score more intuitively, the mean and variance of the AFQT score are obtained and a standard normal is created out of the AFQT score.[14]

---

[13] Before 1989, the AFQT score was equal to the sum of raw scores on the Word Knowledge, Paragraph Comprehension, and Arithmetic Reasoning subtests plus onehalf the raw score on the Numerical Operations subtest. See Kilburn, M. Rebecca, Lawrence M. Hanser, and Jacob Alex Klerman, "Estimating AFQT scores for National Educational Longitudinal Study (NELS) Respondents," United States Dept. of Defense, Office of the Secretary of Defense, Rand Corporation, National Defense Research Institute.

[14] First, if the four subtest scores are X1,X2,X3,X4, then AFQT = X1+X2+2(X3+X4). Second, the mean and variance of the variable AFQT are obtained, mu = mean (AFQT) and v = variance (AFQT). Finally, a standard normal is created out of Y, Z= (AFQT-mu)/sqrt(v), where sqrt is the square root.

The second group of covariates used to control for the heterogeneity of the sample is the family characteristics of respondents. Household income is included because it has a positive effect on youths' labor supply (Goldfarb & Yezer, 1983).[15] All household income figures are deflated using the Consumer Price Index (1997 = 100). As indicated in row (20), adding this variable reduces the sample size sharply due to missing observations. To avoid having to drop a large number of observations, invalid missing values are replaced with the sample mean and validly skipped responses with zero because validly skipped answers come from households without income in the previous year. Other family characteristics include the relationship of the parent figure(s)/guardian(s) in households to the youth; the number of household members under the age of 18 as of the survey date; and parents' education, which is defined as the highest degree that is completed by the parents. Because a large number of respondents refuse, do not know, or skip the question "what was the highest grade of schooling completed by mother/father", all missing values are replaced with the sample mean.

The last group of variables relates to location characteristics. This includes the region of residence and information on whether the residence is in Metropolitan Statistical Area (MSA) as of the survey date. The county unemployment rate is also included because employment depends on the regional labor market. The unemployment rates are for the 1997–2000 time period and relate to the respondent's metropolitan area. The data come from the NLSY97 geocode file.[16] The unemployment rates for 1996 come from the Local Area Unemployment Statistics and are matched with the NLSY97 geocode data file.

---

[15] Goldfarb and Yezer (1983) find that higher household income positively affects hours worked of younger teenagers, while it is insignificant for the older teenagers.

[16] Detail is provided in NLSY97 Geocode Codebook Supplement.

Altogether, there are 22,506 person-year observations, which originate from 7,123 individual youths. The sample construction process and the descriptive statistics of the variables used in the estimation are presented in tables 1.1 and 1.2.

6. Results

6.1 Descriptive Statistics

Tables 1.3 to 1.6 provide information on the distribution of the annual allowance received and the annual hours worked at all types of jobs. Table 1.3 reports the distribution of allowances received by demographic characteristics and by annual hours worked. First, the average allowance received decreases as hours worked increase. This tendency is true for all ages. Youths aged 12 that do not work receive the least $137.03 from parents. Youths aged 16 who do not work receive the most, with a mean allowance of $198.83, while those in the same age group who work more than 1,000 hours per year only receive slightly more than half of that amount. The finding that the average allowance received decreases as hours of work increase is also true for youths of different ethnic origin. For example, youths from the NBNH (Non-black and non-Hispanic) group with average allowance of $154.28 do not work at all, while those that work for more than 1,000 hours per year only receive $69.21. This trend is true also for different genders. In particular, females that work more than 1,000 hours receive only $85.93, while those that do not work receive almost twice that amount at $169.37. Second, compared to other ethnicities, the members of the NBNH group, who are mainly white, receive the least amount of allowance at $141.12. Third, males who work no more than 500 hours per year receive a smaller allowance than females, whereas they get a larger

allowance if they do not work or work different hours. Figure 1.3 relates allowances to gender and hours of work.

TABLE 1.3 ALLOWANCE RECEIVED BY ANNUAL HOURS WORKED AND BY DEMOGRAPHIC CHARACTERISTICS, FROM 1996 TO 2000

Allowance	Full Sample	Annual Hours Worked							
		None		1-500		501-1000		>1000	
	Mean	No.	Mean	No.	Mean	No.	Mean	No.	Mean
Total	159.16	15234	171.50	4900	145.97	1533	113.19	839	96.24
Age									
12	137.14	1483	137.03	5	144	1	260	0	0
13	153.64	2810	155.35	66	101.91	11	60.60	4	61.09
14	164.13	3616	164.68	554	165.61	74	130.48	30	153.42
15	171.69	3781	181.67	1348	153.33	247	134.70	122	140.42
16	160.46	2806	198.83	2137	140.72	791	104.79	368	102.23
17	143.57	682	181.30	705	143.74	362	123.93	261	71.73
18	85.11	56	159.86	85	85.88	47	40.77	54	44.99
Race									
Black	194.63	4067	207.46	1021	168.19	298	134.03	155	149.15
Hispanic	161.31	3423	163.48	818	157.88	233	150.13	127	153.51
NBNH	141.12	7591	154.28	3020	135.15	996	98.72	551	69.21
Mixed	221.74	153	255.96	41	152.03	6	47.08	6	0
Gender									
Male	159.15	7578	173.65	2685	143.45	865	118.30	561	101.36
Female	159.18	7656	169.37	2215	149.02	668	106.58	278	85.93

Notes: There are 22,506 person-year observations in the sample. Full sample refers to the sample of dependent youths.

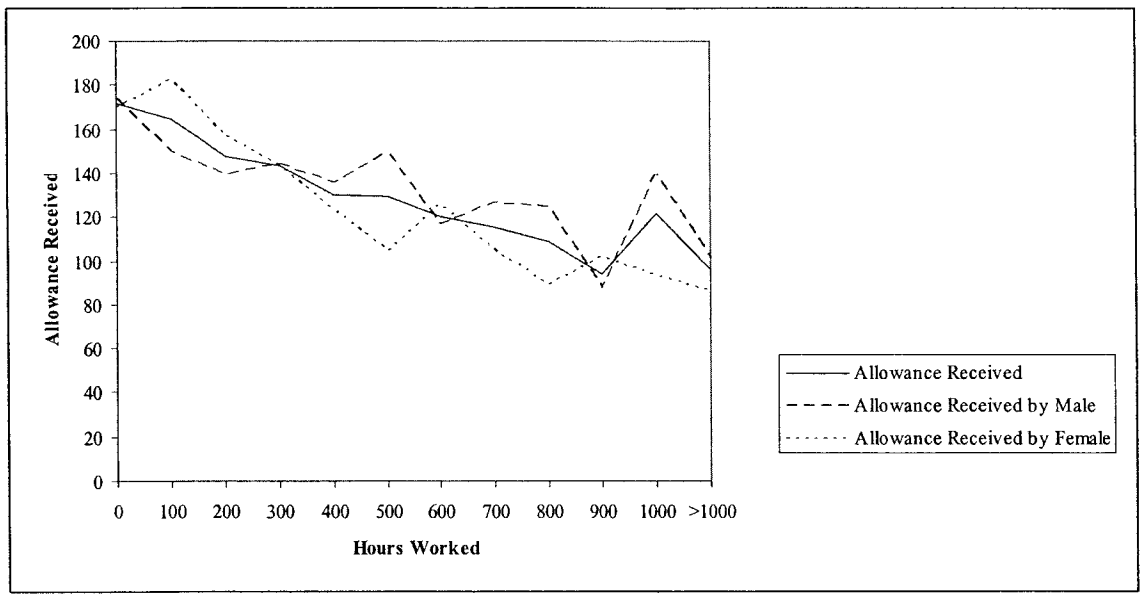

FIGURE 1.3 ANNUAL ALLOWANCE RECEIVED BY HOURS AND BY GENDER

Table 1.4 reports the distribution of hours worked by allowance. Thirty-two percent of youths in the sample participate in the labor force. This percentage is close to the average labor force participation rate among high school students as reported by the Bureau of Labor Statistics for the period from 1996 to 2000.[17] The percentage increases to about 40 percent for those that do not receive any allowance. It is apparent that at higher annual hours of work, a larger percentage of youths do not receive any allowance. This tendency is especially remarkable in figure 1.4. In particular, among those that work more than 1,500 hours per year, 84 percent receive no allowance, while only 52 percent have no allowance among those that do not work. Finally, the last column indicates that more than 42% of youths in the sample receive some allowance. However, table 1.5 indicates that this percentage is larger for youths at a younger age. In particular, 57.69%

[17] The labor force participation rate for persons 16 to 24 years of age enrolled in high school is 38.5%, 42.7%, 40.6%, 41.4%, 39.6%, 40.8%, 41.2%, and 38.7% from 1993 to 2000 (Bureau of Labor Statistics).

and 54.34% of youths at age 12 and 13, respectively, receive an allowance from their parents.

TABLE 1.4 ANNUAL HOURS WORKED BY ALLOWANCE

Allowance	Annual Hours Worked					
	None	1-500	501-1000	1001-1500	>1500	Total
All	15234	4900	1533	583	256	22506
	(67.69)	(21.77)	(6.81)	(2.59)	(1.14)	(100.00)
0	7868	3258	1189	484	214	13013
	(60.46)	(25.04)	(9.14)	(3.72)	(1.64)	(100.00)
	(51.65)	(66.49)	(77.56)	(83.02)	(83.59)	**(57.82)**
1-260	4296	784	146	35	16	5277
	(81.41)	(14.86)	(2.77)	(0.66)	(0.30)	(100.00)
	(28.20)	(16.00)	(9.52)	(6.00)	(6.25)	(23.45)
261-520	1830	454	101	24	12	2421
	(75.59)	(18.75)	(4.17)	(0.99)	(0.50)	(100.00)
	(12.01)	(9.27)	(6.59)	(4.12)	(4.69)	(10.76)
520-2000	1240	404	97	40	14	1795
	(69.08)	(22.51)	(5.40)	(2.23)	(0.78)	(100.00)
	(8.14)	(8.24)	(6.33)	(6.86)	(5.47)	(7.98)

Notes: There are 22,506 person-year observations in the sample. Percentage is reported in the parenthesis. Percentage in higher cell is calculated by dividing the last column and percentage in lower cell is calculated by the dividing the first row.

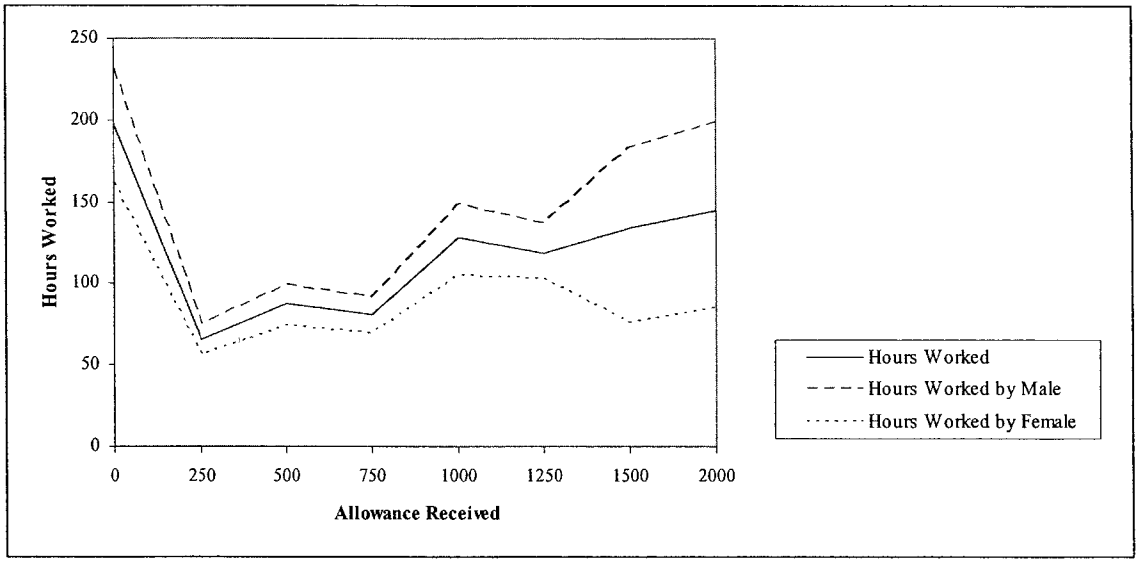

FIGURE 1.4 ANNUAL HOURS WORKED BY ALLOWANCE AND BY GENDER

Table 1.5 reports allowance figures by annual hours worked and demographic characteristics. First, the number of hours worked increases with age. Hours worked increase from a little bit more than one hour at age 12 to more than 584 hours per year at age 18. This is more apparent after disaggregating the full sample into different groups by allowance. For example, youths at age 12 that receive nothing from their parents only work half an hour, while those aged 18 that also receive nothing from their parents work more than 627 hours per year. What is more, at larger allowances the number of hours worked is reduced sharply. For example, for youths aged 16 that receive no allowance the number of hours is 305.75. The number of hours goes down to 182.17 per year for those that receive more than $520 in allowance. Non-Black and Non-Hispanic youths work the most hours when compared with other ethnic groups, with a mean of almost 180 hours annually. There is a significant difference in hours worked between males and females.

For example, males with zero allowance work more than 232 hours, while females without an allowance only work 161 hours per year.

TABLE 1.5 ANNUAL HOURS WORKED BY DEMOGRAPHIC CHARACTERISTICS AND BY ALLOWANCE, FROM 1996 TO 2000

	Full Sample		Annual Allowance Received							
			None		1-260		261-520		520-2000	
	No.	Mean	No.	Mean	No.	Mean	No.	Mean	No.	Mean
Total	22506	149.11	13013	198.17	5277	64.32	2421	88.33	1795	124.71
Age										
12	1489	1.14	630	0.50	656	1.87	150	1.04	53	0
13	2891	9.77	1320	14.73	1040	6.23	385	3.82	146	5.67
14	4274	44.40	2202	56.31	1184	24.94	593	40.88	295	40.60
15	5498	110.82	3174	128.94	1182	76.75	635	108.00	507	80.36
16	6102	258.79	4029	305.75	950	158.18	537	168.10	586	182.17
17	2010	401.13	1456	458.20	247	216.34	112	253.87	195	293.62
18	242	584.63	202	627.21	18	431.89	9	78.78	13	484.62
Race										
Black	5541	117.83	2924	163.31	1383	48.55	637	71.26	597	105.28
Hispanic	4601	112.57	2623	145.55	1131	48.04	469	76.34	378	121.80
NBNH	12158	178.07	7364	231.29	2720	79.63	1277	102.71	797	143.08
Mixed	206	97.19	102	159.27	43	31.42	38	39.39	24	40.30
Gender										
Male	11689	173.74	6734	232.06	2755	73.63	1284	99.19	916	150.65
Female	10817	122.49	6279	161.82	2522	54.15	1137	76.07	879	97.68

Notes: There are 22,506 person-year observations in the sample. Full sample refers to the sample of dependent youths.

Table 1.6 provides information on the distribution of hours worked by location. Youths that live in different regions work different number of hours. The number of hours worked is the largest in the north-central region and the smallest in the western region. The difference in hours worked between the north-central and west is more than

75 hours per year. The table shows that hours worked decrease for larger allowances no matter in which region youths are residing. For instance, youths from the northeast region that do not receive any allowance work almost 200 hours, while those that receive more than $520 per year work less than 120 hours. The result that hours of work decrease as allowance increases holds true no matter whether youths are residing in urban or rural areas. Among youths living in urban areas, youths without any allowance work almost 200 hours per year, while youths with more than $520 work less than 120 hours. Finally, youths living in rural areas tend to work more than those residing in urban areas.

TABLE 1.6 ANNUAL HOURS WORKED BY LOCATION CHARACTERISTICS AND BY ALLOWANCE, FROM 1996 TO 2000

	Full sample		Annual Allowance Received							
			0		1-260		260-520		520-2000	
	No.	Mean	No.	Mean	No.	Mean	No.	Mean	No.	Mean
Region										
Northeast	3894	150.27	2327	198.76	867	68.23	403	69.39	297	119.57
North-central	5097	200.19	3122	259.86	1016	83.44	551	115.49	408	148.65
South	8411	132.64	4929	175.59	2014	54.46	854	72.50	614	127.96
West	5104	124.36	2635	166.78	1380	62.18	613	98.44	476	103.20
MSA										
Urban	18280	143.80	10431	194.21	4317	57.41	2015	86.39	1517	119.34
Rural	4226	172.06	2582	214.16	960	95.42	406	98.00	278	153.99

Notes: There are 22,506 person-year observations in the sample. Full sample refers to the sample of dependent youths.

6.2 Empirical Results

6.2.1 Effects of Allowance and Covariates on Hours Worked

The basic specification (model 1) shows the correlation between allowance and hours of work without covariates. The results from this specification are presented in Column 1 of Table 1.7. The results indicate that hours of work are negatively affected by an allowance. In particular, if the allowance increases by $100 per year, then hours of work decrease by 6.5.

TABLE 1.7 RESULTS OF ESTIMATION ON FULL SAMPLE

Allowance	Model (1) OLS	Model (2) OLS	Model (3) OLS with Covariates	Model (4) Individual Fixed Effects	Random Effects (GLS)
Continuous Allowance	-65.498† (6.971)	—	—	—	—
Low Allowance (0,260)	—	-133.85† (5.46)	-66.627† (5.242)	-45.195† (5.532)	-56.574† (5.090)
Medium Allowance [260, 520)	—	-109.83† (7.41)	-68.690† (6.958)	-69.450† (7.451)	-71.413† (6.684)
High Allowance [520,2000]	—	-73.46† (8.43)	-74.443† (7.895)	-73.162† (9.011)	-78.052† (7.613)
R^2	0.004	0.031	0.164	0.134	0.161
Hausman Test $Chi^2(25)$					192.99
Prob>Chi^2					(0.000)

Notes: There are 22,506 person-year observations. Standard errors are in parentheses. Robust standard errors are reported for the fixed effects model. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

To determine more accurately the causal effect of an allowance on hours of work, the variable allowance is divided into four categories (0, $1-$260, $261-$520, greater than $520). The division is natural because $260 and $520 correspond to $5 and $10 per week,

respectively. The case of *no allowance* is the base category. The hypothesis is that the other three allowance dummies have a negative impact on hours worked and that the reduction in hours worked increases with the size of the allowance received. The results are presented in Column 2 of Table 1.7. The signs are significantly negative as expected, while the magnitude of the reduction is contrary to the above hypothesis. When compared to youths without allowance, those with an allowance greater than $520 work 7.3 fewer hours, while those with an allowance between $260 and $520 work about 11 fewer hours per year. This finding seems confusing because a larger allowance is more likely to cover the consumption needs of youths. If youths work to meet their personal expenses, then those with a larger allowance should be working fewer hours than those with a smaller allowance. The fact that the empirical evidence does not match this expected result is perhaps caused by unobserved heterogeneity and the associated estimation bias or the lack of covariates.

To control for a potential unobserved heterogeneity bias, the first approach is to use a full set of covariates that includes demographic, family, and location characteristics. The results from this strategy are presented in Column 3 of Table 1.7. The effects of the allowance dummies on hours worked are still negative, while the reduction of hours worked increases with the size of the allowance. This result conforms to the hypothesis stated earlier. Relative to the base category, hours worked per year are reduced by 66 hours for youths with an allowance between $1 and $260, while annual hours worked are reduced by 74 hours for youths with an allowance greater than $520. Three different specifications yield consistent coefficients, which confirm that the results are not sensitive to the particular model specification.

Appendix table 1.1 reports the effects of covariates on hours of work. Most personal background variables are significant with the expected signs. Males work 43 more hours than females. Age affects the hours of work significantly. If age increases by one year, then the hours of work will increase by 90. Race also plays a role in the number of hours worked. Non-black/non-Hispanic youths work 68.3 more hours per year than the reference category mixed race/non-Hispanic youths. One possible explanation for this finding is that parents of NBNH children are more likely to have more education and more household income than those of other ethnicities; therefore, they are more likely to live in a neighborhood with more job opportunities (Huang, et. al., 2001 and Rothstein, 2001).[18] Youths with higher AFQT scores work more hours. This finding makes sense, since children with higher intelligence are more likely to perform well in academics and, therefore, have more time available to engage in extracurricular activities, such as part-time work.

Youths may work to support their families in economic hardship. Therefore, household income may be important in determining youths' employment. The base category of the household income variable refers to households with income of greater than $75,000. As previous studies have shown (Huang, et. al., 2001, Rothstein, 2001, and Pabilonia, 2001), parents' income has a positive effect on youths' labor market participation: teenagers from higher income families are more likely to work relative to those from lower income families. The results of this study support these findings: youths

[18] Rothstein (2001) finds that youths living in low income families are less likely to work. She suggests that one of the explanations is they are more likely to live in areas with less economic opportunities, which could restrict their likelihood of working.

from no household income families work 20 fewer hours per year relative to youths from families with incomes of more than $75,000 (Appendix table 1.1).

Parents' education may influence children's employment while in school (Dustmann and Micklewright, 2001 and Pabilonia, 2001).[19] Youths whose fathers completed college work fewer hours than those whose fathers have attained only an elementary or lower level of education (Appendix table 1.1). This tendency is perhaps the result of well-educated fathers having higher career expectations for their children and being concerned with the negative influence of part-time work on academic achievement.

Family structure is important in determining the labor supply (Huang, Pergamit, and Shkolnik, 2001 and Rothstein, 2001).[20] Several variables that characterize family structure are included: the number of children in the family under 6 years of age, the number of children between 6 and 18 years of age, and variables that identify youths that live with both parents or with just one parent. If there are more children in the family, then there will be more financial pressure and more children care responsibilities. The results show that if the number of children between 6 and 18 years of age increases by one, then the number of hours of work decreases by about 7 (Appendix table 1.1). The reduction in hours worked is probably directly related to the additional time that is devoted to taking care of siblings.

---

[19] Dustmann and Micklewright (2001) find parents' education level negatively affects youths' labor supply. They suggest that one of the reasons is that parents worry about the detrimental effects of part-time work.
[20] Huang, Pergamit, and Shkolnik (2001) investigate youths' initiation into the labor market using the NLSY97 data set. They find that youths living in both parents families are less likely to work than those with single parent.

Two dummy variables are employed to indicate whether the father or the mother received any earnings in the previous year. The results indicate that, if a father received income in the previous year, then youths tend to work more hours than if a father did not have income in the previous year. Although the magnitude of this effect is small, it does indicate that parental employment affects children's labor supply.

Dummy variables based on region of residence and residence in an MSA are used to control for location characteristics. Youths in the northeastern, southern, and western region work significantly fewer hours than those in the north-central region. This result may reflect that the most suitable job opportunities for youths are available in this region. Another possible explanation is that youths can work more hours on a farm owned or operated by their parents because this kind of employment relationship is exempted from federal agricultural child labor provisions.[21] This reason may also explain why youths residing in an MSA tend to work fewer hours than youths in a rural area. The local unemployment rate has a significantly negative impact on youths' labor supply. If the rate goes up by one percent, then hours worked will decrease by five per year. This finding reflects that local economic conditions play an important role in determining youths' labor supply.

6.2.2 Fixed Effects vs. Random Effects

The sample of dependent youths is re-examined using individual fixed effects model to control for potential unobserved heterogeneity. Column 4 of Table 1.7 presents the

[21] Detail is in the first chapter of "Report on the Youth Labor Force," 2000, U.S. Department of Labor, Bureau of Labor Statistics, by Alexis M. Herman, Washington, D. C.

estimates from this model. The results of the individual fixed effects model confirm the findings reported in the last section. The estimates for the allowance variables are negative and highly significant at 1 percent level. The magnitudes are remarkably similar to the estimates of the standard OLS model with the full set of covariates except that the effect of a low allowance is reduced from -67 to -45 hours per year in model (3).

The standard errors of the fixed-effects model are based on the assumption that the idiosyncratic errors have a constant variance across t and are not serially correlated within individual units. If the assumption of no serial correlation is rejected for a model, the coefficients would be biased. Therefore, the robust standard errors against heteroscedasticity for the fixed-effects models are reported in this paper.

To test whether a random effects specification is more efficient, the full sample is re-estimated using the random effects model. The results are presented in column 5 of Table 1.7. The random effects estimates indicate that youths with low, medium, and high allowance work approximately 56.6, 71.4, and 78.1 fewer hours per year, respectively, compared to youths without allowance. The comparable individual-fixed effects estimates are 45.2, 69.5, and 73.2 hours. Using two different econometric methodologies, the individual fixed effects and the random effects estimators, the effects of an allowance on hours worked are consistently negative. Since the Hausman test statistics reported in column 5 of Table 1.7 are significant at 1 percent level, the null hypothesis that the random effects model can produce efficient and consistent coefficients is rejected; however, the estimates of the individual fixed effects model are adequate to suggest that

the increase of allowance negatively affect the hours of work and the magnitude of the reduction increases with the allowance.

6.2.3 Full Sample vs. Siblings' Sample

The purpose of this section is to see whether unobserved sibling fixed effects affect the impact of allowance on hours of work. Toward this end, three OLS regressions, the sibling fixed effects, the individual differenced sibling fixed effects, and the random effects models are used. Examining the impact of allowance on hours worked for the sample of siblings is important because the potential bias from unobserved heterogeneity can be eliminated if it is constant between siblings.

Table 1.8 reports the estimates for the sample of siblings. The basic OLS models, model (1), model (2), and model (3), suggest a conclusion similar to that for the full sample. As anticipated, the allowance has a significantly negative effect on hour of work; however, the magnitude of the reduction is slightly smaller than for the full sample. One of the reasons for this is perhaps siblings have more material needs because they may have to share with or show off their earnings to their siblings.

The fourth column presents the results from the estimation of model (5), a sibling fixed effects model. The sibling-difference model corrects for bias due to unobserved family characteristics that are common to siblings. The sibling-difference model is used to examine the effects of an allowance on hours of work between siblings. The results are obtained using data from households with more than one child in the survey. Therefore, youths without a sibling are dropped and the sample size is reduced to 9,263. Compared

to the estimates of individual fixed effects, the estimated effect of an allowance is lower for the sibling fixed effects model (45.20 in column 4 of Table 1.7 versus 39.39 in column 4 of Table 1.8; 69.45 in column 4 of Table 1.7 versus 59.25 in column 4 of Table 1.8). There is one exception: a large allowance has a greater impact (73.16 in column 4 of Table 1.7 versus 78.68 in column 3 of Table 1.8).

TABLE 1.8 RESULTS OF ESTIMATION ON SIBLINGS' SAMPLE

Allowance	Model (1) OLS	Model (2) OLS	Model (3) OLS with Covariates	Model (5) Siblings Fixed Effects	Model (6) Individual Differenced-sibling Effects	Random Effects (GLS)
Continuous Allowance	-68.769† (12.127)	—	—	—	—	—
Low Allowance (0,260)	—	-119.662† (8.814)	-58.454† (8.386)	-39.385† (8.770)	-30.787± (15.702)	-49.430† (8.552)
Medium Allowance [260, 520)	—	-93.731† (12.162)	-56.489† (11.372)	-59.252† (12.290)	-64.012‡ (26.525)	-59.058† (11.482)
High Allowance [520,2000]	—	-66.535† (14.956)	-77.615† (13.986)	-78.678† (15.347)	-78.449‡ (33.358)	-78.275† (13.995)
R^2	0.004	0.023	0.165	0.118	0.054	0.164
Hausman Test $Chi^2(25)$						111.31
$Prob>Chi^2$						(0.000)

Notes: There are 9,263 person-year observations. Standard errors are in parentheses. Robust standard errors are reported for the fixed effects model. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

The fifth column reports the results for the individual differenced sibling fixed effects model. This estimation strategy treats each household and year combination as a distinct panel. That is, each panel at this point contains observations for all the siblings in one family for one year. The fixed effects estimator will then remove the unobserved heterogeneity that affects each family in a year. This approach produces 9,263

comparisons among 5,861 groups. The individual differenced sibling fixed effects model reinforces the earlier results that the impact of an allowance on hours worked is significantly negative and that the magnitude of the reduction increases with the allowance.

Likewise, the siblings' sample is re-estimated using the random effects model. The results reported in column 6 of Table 1.8 confirm that allowance has a significantly negative effect on hours of work. Youths with low, medium, and high allowance work 49.3, 59.1, and 78.4 fewer hours, respectively, relative to youths without allowance. The comparable magnitudes in sibling fixed effects estimates are 39.4, 59.3, and 78.7 hours and in individual differenced sibling fixed effects model are 30.8, 64.0, and 78.4 hours, respectively. Different econometric specifications produce consistently negative estimates. The Hausman test statistics reported in Table 1.8 rejects the null hypothesis at the one percent significance level, which leads to accept the estimates of the sibling fixed effects models. However, the p-value from these specifications is significantly low at 10 percent level, suggesting that siblings do not behave systematically differently from the full sample, although the coefficients of allowance indicate a slightly weaker negative impact on hours of work for the subsample of siblings.

6.2.4 College-bound Versus Non-college-bound Students

To examine the sensitivity of the results to the differences in educational expectations, the full sample is separated into three parts: (1) youths without a high school degree or GED; (2) youths with a high school degree or GED but no college background; and (3) youths enrolled in or graduated from a college. The effect of an

allowance on hours worked may be different for youths with different education or career expectations. Youths with plans to work immediately after high school graduation may want to learn job skills and obtain work experience that expedites their transition from school to high-skill or high-wage careers. Therefore, their incentive to work is more likely to be insensitive to an allowance than that of others. By contrast, youths with plans to enroll in a college may want to save for future study. As a consequence, their incentive to work is likely to be less influenced by an allowance. Estimation on the three sub-samples may reduce the potential bias from unobserved heterogeneity caused by systematically different behavior.

Unfortunately, the variables on the expected educational goals that are provided in the NLSY97 are not suitable for the purpose of this study. For example, data on the percent chance that the respondent will have a four year college degree by age 30 are provided. However, the time lapse between high school graduation and a college degree can be significant. Youths may either enroll in college immediately after high school graduation or return to college after some years of full-time work. Therefore, sample separation depending on this variable may cause those who work after high school and return to college some years later to be included in the sample of youths enrolled in college immediately after high school graduation. Therefore, the criterion used to separate the sample is the enrollment status of respondents in 2002. There are two advantages to employing this variable: (1) in 2002, the oldest respondent is not older than 22, which implies his/her graduation was at most only three years ago; therefore using this variable lessens the potential problem of a significant gap between high school graduation and a return to college; (2) in 2002, the youngest respondents in the sample are not younger

than 18, which implies that most of them have graduated or are at least close to high school graduation; therefore, their educational expectations can be observed.

Table 1.9 presents results estimated by the fixed effects and random-effects models on full sample. The Hausman test is used to determine whether the random effects model is appropriate. The first and second columns report the results and standard errors for youths without high school degrees or GEDs. The Hausman test statistic does not exceed the critical value at the ten percent significance level, which implies no significant difference between the two estimators. Hence, the random effects model produces consistent estimates. The random effects model results indicate that high school dropouts with low, medium, and high allowance work 7.3, 7.3, and 11.6 fewer hours, respectively, when given $100 more allowance per year. The third and fourth columns present results for youths that have high school degrees but are not enrolled in college. The Hausman test yields a value of 35.67, which is significant at the ten percent level. Therefore, the random effects estimator is inconsistent and a fixed effects specification is required. The results suggest that a $100 increase in allowances leads to 3.8, 1.8, and 6.5 fewer in hours of work per year for youths with low, medium, and high allowance, respectively. The fifth and sixth columns show the estimation results for youths that have a college degree or are enrolled in college in 2002. Again, the Hausman test statistic is significant at the one percent level, which rejects the null hypothesis that the random effects model is efficient and consistent. The results for the fixed effects model indicate that if allowances increase by $100 per year, youths with low, medium, and high allowance will reduce hours of work by 4.1, 8.7, and 7.0, respectively. Table 1.9 indicates that youths with a high school degree or GED are the least sensitive to the impact of an allowance. This

may reflect that the main purpose of this group of youths entering the labor market is more likely to gain job experience rather than to earn money for personal consumption. High school dropouts are the most sensitive group of youths to a change in allowance. Their participation in the labor market is more likely driven by the desire to earn money to meet their material needs. The results appear to suggest that they not only have no higher educational goals but also have no plans for future employment. College-bound youths are less sensitive than high school dropouts to a change in allowance but are more sensitive than youths that enter the job market right after high school. This type of behavioral pattern may result because college-bound teenagers have no pressure of having to enter full-time employment right after high school but may want to save some money for college.

TABLE 1.9 RESULTS OF ESTIMATION BY EDUCATION STATUS

		High School Dropout		High School Degree		College Degree	
Fixed Effects Model	Low	*-71.849*[†]	*(34.893)*	-38.691[‡]	(18.736)	-40.892[†]	(10.702)
	Medium	*-67.213*	*(43.430)*	-18.387	(25.190)	-87.405[†]	(14.339)
	High	*-91.586*[±]	*(50.121)*	-64.501[‡]	(29.490)	-70.164[†]	(16.587)
Random Effects Model	Low	-72.831[†]	(15.929)	*-54.899*[†]	*(10.491)*	*-60.849*[†]	*(7.729)*
	Medium	-72.732[†]	(20.799)	*-49.693*[†]	*(13.686)*	*-76.682*[†]	*(10.321)*
	High	-116.002[†]	(23.096)	*-83.707*[†]	*(16.076)*	*-64.885*[†]	*(11.668)*
Number of Obs.			2,839		5,566		9,533
R^2			0.093		0.113		0.133
Prob>Chi^2			0.355		0.082		0.000

Notes: Standard errors are in parentheses. [±] significant at 10 percent level; [‡] at 5 percent level; [†] at 1 percent level. Models included missing dummy variables and an intercept. Italic numbers are rejected because they failed the Hausman test.

6.2.5 Effects of Allowance on the Probability of Labor Force Participation

A set of binary choice models is employed with the same specification as in the last section to identify the impact of an allowance on the probability of youths' participating in the labor market. Table 1.10 present the estimation results for the full sample. Columns 1, 2, and 3 report the estimates of the simple probit model without controlling for unobserved heterogeneity. Columns 4 and 5 report the results for the fixed effects logit model and random effects probit model. Table 1.11 summarizes the results of the fixed effects logit model and of the random effects probit model for the sample that is limited to siblings. The Hausman test is used again to determine whether the random effects probit model is efficient and consistent. The random effects results are reported whenever they are consistent by the criterion of the Hausman test. The estimation results consistently show a significant and negative relationship between the allowance and the probability of working: a larger allowance makes it less likely for youths to participate in the labor force.

Table 1.10 shows that an allowance has a significantly negative effect on the probability of youths' labor market participation. That is, youths with allowance are less likely to work relative to those without allowance. Comparing columns 1 and 2 with column 3, it is apparent that adding a supplemental set of covariates does not change the signs and significance levels of the allowance. However, the magnitude of the impact caused by different levels of allowances on the cumulative normal probability, or z score, of youths' labor force participation is decreased. For instance, when compared to the category of no allowance, the category greater than $520 in model (2) lowers the standard

normal score of labor force participation by about 0.628, while the decrease for model (3) is only 0.340. Coefficients for the sample of siblings in column 1, 2, and 3 of Table 1.11 have a similar pattern. The change in the magnitude of the impact is probably due to the omitted variables problem in models 1 and 2, which results in an upward bias of the estimates. The coefficients of the other explanatory variables are presented in Appendix table 1.4, which generally conform to expectations in model (3). Variables that are statistically significant and positively associated with the probability of employment are age, male, Non-Black and Non-Hispanic, height, AFQT (Armed Forces Qualification Test), "father with a high school degree", and "father or mother having income". The employment probability is negatively impacted if teenagers have a single parent or both parents, if they are residing in the South or West, and by the county unemployment rate.

TABLE 1.10 RESULTS OF ESTIMATION OF PROBABILITIES ON FULL SAMPLE

Allowance	Probit	Probit	Probit with Covariates	Fixed Effects Logit	Random Effects Probit
Continuous Allowance	-0.226† (0.027)	—	—	—	—
Low Allowance (0,260)		-0.628† (0.023)	-0.340† (0.026)	-0.312† (0.103)	-0.659† (0.032)
Medium Allowance [260, 520)	—	-0.428† (0.030)	-0.252† (0.034)	-0.187 (0.127)	-0.568† (0.041)
High Allowance [520,2000]	—	-0.233† (0.033)	-0.286† (0.036)	-0.529† (0.137)	-0.371† (0.044)
Log-Likelihood	-14126.042	-13722.712	-10746.853	-1840.346	-11,962.811
Hausman Test $Chi^2(25)$					674.03
$Prob>Chi^2$					0.0000
No. of Observations				12,327	

Notes: There are 22,506 person-year observations except that the fixed effects logit model dropped 10,179 observations due to all positive or all negative outcomes. Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

The results estimated by the fixed effects logit models for the full sample and siblings' sample are reported in columns 4 of tables 1.10 and 1.11. The coefficients indicate that a higher allowance discourages the labor force participation of youths. For example, for the individual fixed effects logit model, the log-likelihood of labor market participation of youths having an annual allowance of more than $520 is lowered by 0.529, and that of youths with an allowance less than $260 is lowered by 0.312 than that of teenagers without an allowance. The log-likelihoods for the sibling fixed effects logit models follow a similar pattern. There is, however, one exception. The coefficient of the allowance variable loses its significance in the individual fixed effects model for the allowance range between $260 and $520.

TABLE 1.11 RESULTS OF ESTIMATION OF PROBABILITIES ON SIBLINGS' SAMPLE

Allowance	Probit	Probit	Probit with Covariates	Fixed Effects Logit	Random Effects Probit
Continuous Allowance	-0.223† (0.046)	—	—	—	—
Low Allowance (0,260)		-0.601† (0.036)	-0.376† (0.042)	-0.586† (0.109)	-0.686† (0.051)
Medium Allowance [260, 520)	—	-0.363† (0.047)	-0.201† (0.053)	-0.511† (0.137)	-0.527† (0.065)
High Allowance [520,2000]	—	-0.196† (0.056)	-0.313† (0.062)	-0.522† (0.158)	-0.357† (0.076)
Log-Likelihood	-5834.762	-5687.087	-4380.560	-1777.222	-4908.781
Hausman Test $Chi^2(25)$					273.40
$Prob>Chi^2$					0.0000
No. of Obs.				7,523	

Notes: There are 9,263 person-year observations except that the fixed effects logit model dropped 1,740 observations due to all positive or all negative outcomes. Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

Columns 5 of Table 1.10 and Table 1.11 present the results estimated by the random effects probit model for the full sample and siblings' sample, respectively. These two columns consistently show that youths with higher allowance are less likely to participate in the labor force. However, the Hausman test statistics reject the hypothesis that the random effects probit estimator is efficient and consistent. Therefore, the marginal effects are computed based on the fixed effects logit model.

To measure the impact of a unit change in allowance on the probability of labor force participation, Table 1.12 reports the marginal effects for the fixed effects logit model. The results show that youths with a larger allowance have a consistently lower probability of participating in the labor force than do youths without allowance. In particular, if youths were moved from the *no allowance* to the *low allowance* ($1 to $260) category, then the response probability of participating in the labor force would be 19.3 percentage points lower. Similarly, the probability that youths with a *medium allowance* ($261 to $520) or a *high allowance* ($520-$2000) participate in the labor force would decline by 17.6 or 11.3 percentage points if one went from the *medium* or *high allowance* to the *no allowance* category. It is interesting to note that the probability of youths' labor force participation does not decrease monotonically as the allowance increases. This finding may be a result of the law of diminishing returns: an additional dollar increase may mean nothing to rich youths but a lot to poor youths. The results for the siblings' sample show similar results. Youths with an allowance have a lower probability of labor force participation. The negative relationship between allowance and the probability of labor market participation is robust to different econometric

specifications regardless of what sample is used. Therefore, siblings do not behave systematically different than the full sample.

TABLE 1.12 MARGINAL EFFECTS OF FIXED EFFECTS LOGIT MODEL

Independent Variables	Full Sample		Siblings Sample	
Low allowance	-0.193†	(0.052)	-0.239†	(0.042)
Medium Allowance	-0.176†	(0.052)	-0.214†	(0.051)
High allowance	-0.113†	(0.034)	-0.136†	(0.038)
Male	—	—	0.090	(0.020)
Black	—	—	-0.032	(0.289)
NBNH	—	—	0.036	(0.268)
Hispanic	—	—	-0.149	(0.265)
Grade	0.001	(0.003)	-0.001	(0.005)
AFQT	—	—	0.130†	(0.013)
No household income	0.140†	(0.040)	0.032	(0.036)
Low Household income	0.075	(0.046)	-0.001	(0.051)
Middle household income	-0.003	(0.043)	-0.042	(0.050)
High household income	-0.019	(0.043)	-0.056	(0.054)
Mother completed high school	—	—	-0.048	(0.135)
Mother completed college	—	—	-0.156	(0.186)
Father completed high school	—	—	0.342†	(0.130)
Father completed college	—	—	0.124	(0.172)
Have both parents	-0.083±	(0.044)	-0.042	(0.055)
Have single parent	-0.050	(0.039)	-0.050	(0.054)
Number of siblings between age 6 & 18	-0.180†	(0.039)	-0.130†	(0.011)
Number of siblings under age 6	-0.091†	(0.026)	-0.049±	(0.026)
Mother has income	0.205†	(0.052)	0.210†	(0.029)
Father has income	0.194†	(0.052)	0.260†	(0.042)
South	0.064	(0.123)	-0.013	(0.160)
North-east	-0.209‡	(0.088)	-0.292	(0.211)
West	0.075	(0.151)	0.080	(0.157)
MSA	-0.192†	(0.065)	0.073	(0.075)
County unemployment rate	0.000	(0.000)	0.000	(0.000)
Number of Observations		12,327		7,523

Notes: Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept. To obtain the marginal effects of fixed effects logit model, I dropped *age* and *height* to avoid the rescaling problem. Marginal effects for dummy variable are the discrete change from 0 to 1.

7. Conclusion

With approximately 35 percent of high school students participating in the labor market, researchers have focused on the consequences that part-time work has on academic, behavioral, and employment outcomes. However, there has been little academic work so far on the incentives that drive students to seek employment while they are still in school. The purpose of this study is to start to fill this gap in the literature by examining the effects that an allowance from the family has on youths' incentives to work. Work is interpreted to mean both hours worked and the probability of participation in the labor force.

A theoretical model based on utility maximization is developed to frame the study and to examine through what channels an allowance may affect the incentives of labor force participation. Econometric evidence on the connection between allowances and work relies on data from the National Longitudinal Survey of Youth 1997. A number of alternative models of the fixed effects and random effects type are estimated.

The results from the basic specification suggest that allowances in fact do negatively affect hours worked of youths. Youths would consume more leisure and work less if they received a larger allowance. This result is consistent with the standard work-leisure model. A larger allowance also discourages the probability of participation in the labor force.

However, the estimates from the basic model may be biased due to unobserved heterogeneity. To explore the existence of such a bias, individual fixed, sibling fixed, and

individual differenced sibling fixed effects models are estimated. The results from these models largely confirm the findings derived from simple OLS estimates. They also show that the magnitude by which the number of hours worked is reduced is not the same for different allowance levels. In particular, at higher allowance levels the number of hours worked goes down the most, while at lower allowance levels the number of hours worked is reduced by much less. The conclusions derived from a set of econometric specifications are consistent. Therefore, the results are not sensitive to the particular econometric specification used.

Fixed effects logit and random effects probit estimators are used to control for unobserved heterogeneity in the models that try to explain the probability of youths' labor force participation. The marginal effects calculations show that an allowance negatively affects youths' incentives to work regardless of what sample is used. In particular, youths that receive some allowance are 11 to 19 percentage points lower for the full sample and 14 to 24 percentage points lower for the siblings' sample on the probabilities of participating in the labor force than those teenagers that do not receive an allowance.

The investigation of the sensitivity of results to different educational status shows that youths with high school degrees or GEDs are least insensitive to allowance, while high school dropouts are most sensitive to allowance. This conclusion suggests that the effects of allowance on youths' employment behavior, to some extent, depend on the educational expectations of youths.

From a theoretical perspective, the results allow for a better understanding of factors that influence youths' entry into the labor market. One of the reasons for the lack of consensus on the impact that work has on youths that attend school on a full-time basis is that previous studies have not captured youths' incentives to enter the labor market. This shortcoming can lead to the problem of omitted variable or unobserved heterogeneity bias, which complicates any evaluation of the impact of youth employment. From a practical perspective, the results have some potentially important policy implications. In particular, they provide empirical evidence that can be used in the development and implementation of future School-to-Work programs. For example, the results show that the labor market behavior of youths without high school degrees or GEDs is very sensitive to the impact of an allowance. If a future STW program would give them not only an opportunity to learn a technical skill but also provide them with the financial means to fulfill their personal needs, one would predict that dropout students will be attracted into the program. By entering and remaining in the program, those dropout students could achieve much needed work experience and job skills that would increase their chances of employment and facilitate their transition from school to a world of work.

Chapter II

Estimating the Effect of Participation in School-to-Work Programs on Wages

1. Introduction

In 1994, President Clinton signed the school-to-work Opportunities Act awarding federal grants of $300 million for fiscal year 1995 and equal amounts available for fiscal years 1996 through 1999 to the states and localities to develop school-to-work systems. The passage of this law was spurred by the findings that (1) 75 percent of students in the United States attempt to enter the labor market directly from high school without pursuing baccalaureate degrees and many do not have the knowledge and skills needed to work; (2) there are a significant number of youths in the United States, especially disadvantaged students and students with disabilities, who drop out of high school without a high school degree; (3) high school graduates suffer a high unemployment rate and low earnings relative to individuals with more education; (4) unskilled and less skilled youths face a more unfavorable situation in an environment of intense international competition and complex new technologies, which reduces the demand for unskilled labor and weakens their earning power; (5) the United States does not provide a systematic scheme that prepares these untrained youths with academic and technical skills necessary to succeed in postsecondary education and entry into the workforce of the 21st Century (School-to-Work Opportunities Act, 1994).[22]

These problems led Congress to recognize the failures of America's education policies and to conclude that to create efficient paths for students to follow to move from school to stable jobs or from school to continued education and training, a national effort

[22] The findings are summarized from Section 2 in School-to-work Opportunities Act of 1994.

is required to develop a coherent school-to-work system to assist students' transition from school to the adult workplace. Therefore, the School-to-Work Opportunities Act focuses on helping students attain academic, technical, and life skills that can be applied in the world of work. Specifically, the purposes of this act are to (1) promote the building of partnerships among schools, businesses, and communities to facilitate the school-to-work transition; (2) integrate educational and occupational learning to improve knowledge and skills; (3) integrate school-based and work-based learning.

In 2001 the School-to-Work Opportunities Act (STWOA) phased out. Since then, it has not been reauthorized by Congress. As a result, there is no federal funding available for states. State decision-makers have to identify whether the school-to-work programs have been effective before they determine to continue with these programs. However, there is very little evidence on the effectiveness of the programs. One reason is that the school-to-work program is comparatively new and no large dataset is available that records participants' transition from school to work. In addition, it is difficult to set up a comparison group of non-participants to identify the impact of the programs.

This study attempts to address the effectiveness of one of the major initiatives—"prepare the students for first jobs in high-skill, high-wage careers".[23] Participation in school-to-work programs provides students with occupational skills, which would, in turn, increase the human capital and the chances that students can work in an environment that requires more skills or matches their interests (Orazem and Mattila, 1986). This study will examine whether youths participating in school-to-work programs earn higher wages in their first primary job immediately after high school graduation than those who do not. This study seeks to fill the gap in the literature pertaining to this topic.

[23] School-to-Work Opportunities Act of 1994: Section 3, (a)(1)(C)(ii))

The following questions will be addressed in order to evaluate the effectiveness of the school-to-work program:

(4) Does participation in school-to-work programs increase the hourly wage of youths in their first real jobs after high school graduation?

(5) Which program is more efficient in performing this initiative, school-based or work-based programs?

(6) Is the effect of participation in school-to-work programs greater for males or females? That is, are there gender differences in the effect of participation in a training program?

This study will provide empirical evidence on how effectively school-to-work programs accomplish one of their major objectives—increasing the earning power of students in their first primary jobs. The empirical evidence will be valuable to state policy-makers and educational legislators. It will also be helpful to educational developers and planners in making decisions about future implementation and reform of the school-to-work program.

The organization of this chapter is as follows: section 2 reviews the literature; section 3 provides the theoretical background; section 4 describes the data set and sample selection process; section 5 develops the empirical model; section 6 reports the empirical results; and section 7 discusses the policy implication and conclusions.

2. Literature Review

The effectiveness of school-to-work (STW) programs has yet to be determined. One reason is that STW involves most or all students and it is difficult to find a randomly selected treatment group to compare with a control group (Hershey et. al., 1999).

Moreover, STW is relatively new and no large representative statistical information is available for researchers to use. As a result, very few studies have conducted systematic analyses to determine the extent to which the STW program has achieved its objectives.

Hershey et. al. (1999) conduct a relatively thorough evaluation of the school-to-work program implementation.[24] The report evaluates the goals of (1) promoting state and local partnerships to create and support School-to-Work Opportunities systems; (2) increasing the opportunities of changing students' educational experiences; and (3) involving students with diverse backgrounds using surveys of all local partnerships from late 1996 to 1999 and surveys of students conducted in eight states from 1996 to 2000. Their reports indicate that STW programs expose students to a wide range of industries and increase their opportunities to work in an environment relevant to their interests and career goals. However, they conclude that the STW program made less progress compared to the expectations of congress.

Riggio and Riggio (1999) conduct an evaluation of the school-to-work programs using the first round survey of National Longitudinal Survey of Youth 1997 (NLSY97) database. They first examine the differences of pre-treatment variables between participants and non-participants. Then they use an analysis of covariance (ANCOVA) to control simultaneously for those variables. They find that (1) the participation in any school-to-work program has a positive effect on part-time job income; (2) there is a positive influence of participating in STW program on job seeking behavior; (3) participation in school-to-work programs positively affect students' future expectations such as the probability of finishing high school or obtaining a college degree; (4) there is

[24] This is a report prepared for U. S. Department of Education, Planning and Evaluation Service conducted by Mathematica Policy Research, Inc.

no significant impact on reducing delinquent behaviors of participants. Additionally, they find the program of job shadowing has a greater positive effect than any other STW program. Particularly, the participants in the job shadowing program are more likely to work or look for work during the month before the survey and have more positive expectations for the future.

Neumark and Joyce (2001) use the first wave of the NLSY97 to evaluate school-to-work program implementation. They use proxy variables, school fixed effects, and instrumental variable methodologies to control for the selection problem. They first assume that particular types of school-to-work programs have the same effects on educational and labor market outcomes; therefore they lump all components of school-to-work program together. Their results indicate that participation in STW programs (1) does not have an impact on current enrollment, current employment, and hours or wages of part-time work; (2) has positive effects on the probability of working more than 20 hours per week in the next year; (3) increases the probability of taking college-preparatory tests such as SAT or ACT; (4) positively affects youths' working more than 20 hours at age 30, but not significantly on youths' obtaining a high school diploma by age 20 and a four-year degree by age 30. Moreover, they categorized school-to-work programs according to the hours spent on each type of STW program at work sites. In doing so, they find that there are no significantly different effects across each category of STW program on outcomes when compared to the scheme of grouping all school-to-program together.

Stone (2002) uses Ordinary Linear Squares (OLS) to examine the impact of participation in STW programs on student academic achievement and behavioral patterns

including grade point average (GPA), high school graduation, college attendance, future work aspirations, school attendance, and risky personal behavior using the first and second rounds survey of NLSY97. First, the results show that there is no effect of participation in STW program on self-reported GPA. Next, participation in STW programs does not appear to affect the expectations of post high school working hours and college aspirations. Then, there is no association between the participation in STW programs and school attendance and tardiness. Finally, STW participation does not affect the probability of engaging in risky behaviors such as having sex, smoking, drinking, and using marijuana.

The literature suffers some shortcomings, which probably cause the results to be biased or less useful to policy makers. First, few studies have focused on the impact of participation in STW on labor market outcomes immediately after completion of the program. However, this period is the most important in determining whether participation in STW training programs is effective in affecting employment outcomes of the STW graduates because STW participants and non-participants have the same high school experience in terms of schooling and working. The only difference that accounts for their competency to an employer is whether they have received any training towards their future careers, which is a good signal indicating that they are qualified to work. Second, existing studies regard individuals as randomly selected into the STW program (Hershey, et al., 1999). However, the choice to participate in a STW program can not be considered exogenous in modeling career choices, since the decision may be affected by individual characteristics, such as unobserved ability or family background. These factors complicate any evaluation of the impact of the STW program. Third, previous studies are

only concerned with the effects of participation versus non-participation and do not distinguish the effects of participation in particular types of programs. However, it is important for researchers and policy makers to determine which STW programs are effective in preparing youths for a career and what programs need to be improved to achieve this goal. Finally, previous researchers are restrained by data availability; therefore, a few dependent variables are not based on observations that have occurred but on the youth's beliefs about events that may occur in their future. For example, respondents are asked to predict the probability that they will work more than 20 hours per week (*i*) one year from the interview if they are in school then and (*ii*) at age 30. The problem of using predicted future work and schooling behavior as a dependent variable is that current expectations that highly depend on their values and beliefs may not materialize. If youths have positive forward-looking attitudes, then they will work hard to accomplish great things. Therefore, attitudes are very likely to influence the decision to participate in such training programs because training is a way to achieve lifetime aspirations. As a result, using subjective expectations as dependent variables without considering unobserved personal attitudes could lead to biased estimation results for the effect of school-to-work programs.

This chapter will contribute to the existing literature on how participation in school-to-work programs affects wages in the first job immediately following high school graduation in several ways. First, this chapter uses a new longitudinal data set, the NLSY97, which has extensive information on school-to-work programs, such as the types of programs in which youths participated. Second, a recently developed propensity score matching method is used for the empirical analysis, which allows for a more

satisfactory analysis of non-experimental data. Third, separation of school-to-work programs by work-based and school-based activities makes it possible to explore which program type is more effective in increasing wages of participants.

3. Theoretical Model

In this section, a model that is widely used in the training program evaluation literature is used to predict the impact of participation in school-to-work programs on labor market outcomes such as wages, employment probability, and occupation choices. A prospective trainee's decision to enroll in a training program is governed by the returns, the expected present value of earnings with and without training, and the cost, training, and foregone opportunity earnings, in an environment of perfect information.[25]

Suppose an individual receives training in period k, which takes one period to complete. The training is available to all individuals at only one period k and they have the freedom to choose to participate. However, the opportunity to train will not occur again once it has elapsed. W denotes the wage that an individual receives from working, t denotes the period, ϵ is the mean zero random disturbances and X is exogenous with respect to ϵ, δ is a training indicator and α is the impact of training on wages. Assume δ is uncorrelated with ϵ. The earnings of an individual who trains in period t are

$$(1) \qquad W(t) = \begin{cases} X(t)\beta + \delta\alpha + \varepsilon(t) & t > k \\ X(t) + \varepsilon(t) & t \leq k \end{cases}.$$

An income maximizing individual compares the present value of earnings with and without training in an environment with a discount rate r, which is assumed to be

[25] Details are in Handbook of Econometrics, Volume III, James Heckman and Tomas E. MaCurdy.

constant. The participation decision, therefore, actually depends on the expected discounted values of all earnings streams.

The present value of earnings for an individual without training as of period k is

$$(2) \qquad PV_0 = \sum_{j=0}^{\infty}\left(\frac{1}{1+r}\right)^j W_n(k+j)$$

There are no earnings in period k for trainees; therefore, the present value of earnings for an individual with training is

$$(3) \qquad PV_1 = S + \sum_{j=1}^{\infty}\left(\frac{1}{1+r}\right)^j W_m(k+j)$$

$$= S + \sum_{j=1}^{\infty}\left(\frac{1}{1+r}\right)^j W_n(k+j) + \sum_{j=1}^{\infty}\frac{\alpha}{(1+r)^j}$$

where S denotes the subsidy or cost incurred in the training period (e.g. training allowance or tuition payment), α is the amount of earnings increased by training per period.

The decision to participate in a training program is based on a comparison of the present value of earnings with and without trainings.

$$(4) \qquad PV_1 - PV_0 = S - W(k) + \frac{\alpha}{r}$$

Therefore,

$$(5) \qquad \delta = \begin{cases} 1 & if \quad S - W(k) + \dfrac{\alpha}{r} > 0 \\ 0 & otherwise \end{cases}$$

Since the individual is only interested in discounted present earnings, he or she will participate in the training program if $PV_1 - PV_0 > 0$.

4. Data

Data from the National Longitudinal Survey of Youth 1997 (NLSY97) are used to analyze the impact of participating in school-to-work programs on the hourly wage in the first primary job after high school graduation. The NLSY97 is used because it collects a variety of information on school-to-work programs and their participants, such as their labor market behavior and schooling experiences. The NLSY97 includes 8,984 young men and women who are aged 12-16 as of December 31, 1996. The sample is composed of a cross sectional sample of 6,748 respondents who represent people living in the United States during the initial round and a supplemental sample of 2,236 Hispanic and black people. Respondents have been interviewed annually since 1997 and the survey is in progress. The survey is weighted to be a nationally representative sample.[26] In this paper, data come from the first five waves (1997-2001).

The survey collects school-to-work programs and employment data as an event history retrospectively starting with the interview week. In the first round, youths who are in the 9th grade or higher are asked a number of questions about "programs that schools offer to help students prepare for the world of work." In later rounds, these questions apply to all who attended school since the date of their last interview. The information includes whether the respondent participated in a "career major" program since the date of their last interview, which is "a defined sequence of courses based upon an occupational goal" (NLSY97 Questionnaire), and what kind of program the respondents participated through their school graduation. The program can be divided into three components:

a. School-based activities

[26] In this paper, the sample is not weighted to be national representative.

School-based learning is a program of classroom instruction and curriculum that integrates high academic standards with the knowledge and skills necessary to prepare a student for postsecondary education and the requirements necessary for a student to earn a skill certificate. It may involve two activities:

a) Cooperative education

The program provides a practical way to apply and strengthen knowledge learned in academic and technical studies and to gain real world-of-work experiences.

b) Tech prep

The program offers rigorous curricula within the context of applying content in "hands-on" learning experiences. It prepares students for technical careers and other postsecondary educational experiences in technical and four-year colleges.

b. Connecting activities

The connecting activities component connects school-based opportunities with work-based opportunities by building a bridge between school and work.

c. Work-based activities

Work-based learning, as the main component of school-to-work programs, is a planned program of job training and work experience that is coordinated with the school-based activities. They include internship/apprenticeship, job shadowing, workplace mentoring, and working at a school-education enterprise activities. In detail, they are composed as follows:

a) Apprenticeship or internship

The program is designed to help students learn about a particular occupation or industry by working for an employer.

b) Job shadowing

The program offers students an opportunity to observe and experience how businesses and industries function at work sites.

c) Mentoring

The program is designed to match students with a professional in a chosen career for a defined period of time.

d) School-sponsored enterprise

The program offers students an opportunity to produce goods or services for sale or use by others.

This analysis is based on whether respondents participate in school-to-work programs. Therefore, respondents who do not answer the question about their participation in any school-to-work programs are dropped.[27] The NLSY97 distinguishes between four types of employments: employee-type jobs, freelance jobs,[28] self-employment, and military service. In this study only youths with employee-type jobs are considered, where the respondent has an ongoing relationship with a specific employer. Youths aged 14 and older are asked about the job's characteristics as of the time they started that job. The employment section includes the beginning and ending dates of all employee-type jobs, gaps within employee-type jobs and gaps between jobs, the total number of hours worked in each week at a civilian job beginning with the week the respondent turned 14, the three-digit occupation code for each job, and the hourly rate of

[27] Respondents that do not answer the question include those who do not know the answer, refuse to reply, and those who should reply but invalid skipped questions.

[28] Freelance jobs are those for which the respondent performed one or a few tasks for several people without a specific boss, or in which the respondent worked for himself or herself, such as lawn-mowing and baby-sitting,

pay as of the job's stop date. If the job lasted 13 weeks or less, then the hourly rate of pay is as of the job's start date.

(1) Dependent variable: Hourly rate of pay in the first (primary) job

To be considered a primary job, two requirements must be met. The first requirement is that the stop date of the job must be greater than the graduation date from high school. Because the event history records the end date of each employee-type job and the month of graduation from high school, it is possible that January 1, 1995 can be set as the first week and the end date of each job and graduation month can be converted into a continuous week number. Those respondents with invalid responses are dropped. For those who answer the start or stop year of their job but miss the start or stop day/month, missing start days are imputed to 1 and missing stop days to 28 and missing start months to January and missing stop months to December (Mainfile Codebook Supplement). The second requirement is that the job must be worked full time, where the "usual number of hours worked in the week on a single [main] job is at least 30 hours" (Wolpin, 1992). For simplicity, the working hours per week are assumed to be constant (NLSY97 codebook supplement); thus, the hours worked in the start week are compared to 30. If it is greater or equal to 30, then the job is considered full time.

The hourly rate of pay is one dependent variable of interest, which reports the hourly rate that respondents earned. This variable excludes overtime and performance pay. Hourly monetary compensation is the other dependent variable, and it includes any non-wage or non-salary pay such as overtime, tips, commissions, and bonuses. Both variables record the respondent's compensation as of the job's stop date for each job lasting 13

weeks or more (or at the time of the survey for on-going jobs). If the job lasts 13 weeks or less, then the hourly rate of pay is as of the job's start date.

Table 2.1 presents the sample used and describes the process of sample construction. The original NLSY97 sample consists of 8,984 individuals. Of these, there are 2,895 youths who hold a first job meeting the full-time job requirements, of which 1,377 were male (Table 2.2).

TABLE 2.1 SAMPLE CONSTRUCTION

	Number of Observations
(1) Total observations	44920
Condition on Key explanatory variable	
(2) drop invalid "STW program" responses	43670
Condition on other explanatory variables	
(3) (2) drop invalid "ASVAB score" responses	43510
(4) (3) drop invalid "8th grade GPA" responses	43405
(5) (4) drop invalid "# of children under age 6 and age 6-18" responses	40233
(6) (5) drop invalid "household size" responses	40225
(7) (6) drop invalid "MSA and region" responses	40066
(8) (7) drop invalid "parents income" responses	38641
(9) (8) eligible for high school graduates requirement	9703
(10) (9) eligible for first real (primary) job requirement	4980
(11) (10) with valid answer for hourly wage	2895
(12) (11) with valid answer for hourly compensation	2738

Notes: Invalid responses include 'invalid skip', 'I don't know', and 'refuse to answer'. The lowest and highest 1% of hourly wages is replaced with the rate of wage at 1% and 99%, respectively.

(2) Independent variables

To control for the pre-treatment differences that may affect participation in school-to-work programs, several groups of variables are included as covariates in the econometric specification.

The first group of covariates controls for the respondents' personal background characteristics such as gender, age, race, and ethnicity. Previous school performance such as the marks received in 8th grade is also included. Past academic accomplishments are likely to influence the educational expectations of the respondents. In that sense, if respondents have poor GPAs in the 8th grade, they may consider themselves as non-college material so that they may self-select into STW programs to gain necessary marketable skills to be competitive in the job market after high school graduation. Therefore, including this variable could reduce unobserved heterogeneity. Grades are measured on a 4.0 scale from 'mostly Ds' to 'mostly As'. The grades such "As to Cs", "mixed", "ungraded", "skipped 8th grade", and "other" are replaced with the sample mean.[29] As Rows (8) and (9) indicate, adding this group of variables does not reduce the sample size substantially.

Expected earnings are based on innate ability (Beyer and Knight, 1989 and Robertson and Symons, 1990). Therefore, if an individual's intelligence is not controlled in the specification, then the estimates on the return of participation in STW programs would be biased. In the previous research, Armed Force Qualifications Test (AFQT) score is employed because it not only indicates whether individuals are qualified for enlistment but it also predicts initial success in the civilian labor force (NLSY Users' Guide). However, the NLSY97 does not provide the AFQT score in the fifth survey wave. Fortunately, AFQT is a composite score from four selected tests of Armed Services Vocational Aptitude Battery (ASVAB). The ASVAB contains 10 power and 2 speeded tests, which measure the vocational aptitude of the respondents in the areas of reading

[29] Grades received in the 8th grade include mostly below Ds=0.5, mostly Ds=1, about half Cs and half Ds=1.5, mostly Cs=2, about half Bs and half Cs=2.5, mostly Bs=3, mostly about half As and Bs=3.5, As=4. As to Cs, mixed, ungraded, skipped 8th grade, and other are replaced with the sample mean.

comprehension, word knowledge, mathematical knowledge, and numerical operations. The AFQT score is the sum of the scores from the arithmetic reasoning and math knowledge subtests plus twice the sum of the standard scores on the paragraph comprehension and word knowledge subtests.[30] The ability estimates for each subtest may have positive or negative values. A lower score indicates a poorer performance and a higher score indicate a better performance. There are 7,127 respondents who completed this test during the first round, which accounts for 79.3 percent of the NLSY97 sample (NLSY97 codebook supplement, appendix 10). The respondents who invalidly skip the questions are deleted and those who validly skip the questions are replaced with the sample mean.[31] To interpret the coefficient of the AFQT score more intuitively, the mean and variance of the AFQT score are obtained and a standard normal is created out of the AFQT score.[32]

The second group of independent variables controls for the family characteristics, which include *Parents' Income*, *Parents' Education*, etc. Orazem and Mattila (1986) indicate that family wealth is used to control for home inputs into the education production. If that is the case, then higher household incomes should have a positive effect on earnings. That is, youths from higher household income families are expected to earn more. All respondents who live with a parent at the interview date are eligible to

---

[30] Before 1989, the AFQT score was equal to the sum of raw scores on the Word Knowledge, Paragraph Comprehension, and Arithmetic Reasoning subtests plus one half the raw score on the Numerical Operations subtest. "Estimating AFQT scores for National Educational Longitudinal Study (NELS) Respondents", M. Rebecca Kilburn, Lawrence M. Hanser, Jacob Alex Klerman, United States Dept. of Defense Office of the Secretary of Defense, Rand Corporation, National Defense Research Institute.

[31] Invalid skipped observations are from those who have completed the test but have not provided the responses. Valid skipped observations are from those who do not take the test.

[32] First, if the four subtest scores are X1,X2,X3,X4, then AFQT=X1+X2+2(X3+X4). Second, the mean and variance of the variable AFQT are obtained, mu=mean (AFQT) and v=variance (AFQT). Finally, a standard normal is created out of Y, Z= (AFQT-mu)/sqrt(v), where sqrt is the square root. Before 1989, the AFQT score was equal to the sum of raw scores on the Word Knowledge, Paragraph Comprehension, and Arithmetic Reasoning subtests plus one half the raw score on the Numerical Operations subtest.

have this questionnaire administered. It collects the parent's total pre-tax income from wages, salaries, commissions, and tips during the past calendar year; the same data for the parent's spouse or partner; and the total pre-tax amount of any other income received (i.e., farm or business income, inheritances, child support, government programs). All household income figures are deflated using the Consumer Price Index (1997 = 100).

The survey collected information about *Parents' Education* such as the highest grade completed by the respondent's parents. Dummy variables are used to categorize parents' schooling into basic, intermediate, and high levels of education.[33] If parents' schooling level is related to the mental ability of children, then parents with higher education may be related to higher wages. Not all respondents provide their highest grade of schooling. For example, fathers of 6,743 respondents or 75 percent of the sample answered their highest grades completed and the rest do not respond to or validly skip the question.[34] Thus, to maintain a sufficient sample size, the validly skipped responses are replaced with the sample mean and the respondents who provide "refuse" or "do not know" answers are dropped.

Other family background variables include the relationship of the parent figures/guardian in the household to the youth, household size, number of household members under age 6 and the number between age 6 and 18, and two dummy variables indicating whether parents have any earnings or income from a job, farm, business or professional partnership.

---

[33] Parents with basic level of education refer to those without high school degrees including no education, which is the base category for this group of variable. Parents with intermediate education refer to those with high school degrees. Parents with high level of education are those with at least some college degrees.
[34] Respondents who valid skip the question of highest education completed are those.

TABLE 2.2 DESCRIPTIVE STATISTICS OF DEMOGRAPHIC CHARACTERISTICS AND OUTCOME

Characteristics	STW Program Participants		STW Program Non-participants		ANOVA
Outcome Variables:					
Hourly Wage	7.496	(2.870)	7.222	(2.516)	
Hourly Compensation	8.384	(4.214)	7.993	(3.608)	
Explanatory Variables:					
Age	17.811	(0.782)	17.832	(0.785)	
Male	0.473	(0.499)	0.482	(0.500)	
Non-black and Non-Hispanic (White)	0.562	(0.496)	0.598	(0.491)	*
Black	0.247	(0.432)	0.194	(0.396)	***
Hispanic	0.181	(0.385)	0.203	(0.403)	
GPA in 8th grade	2.997	(0.752)	2.977	(0.709)	
AFQT	-0.006	(-0.985)	0.014	(1.036)	
Gross household income	25332.71	(44133.2)	25224.93	(42360.68)	
>12 Highest grade completed by mother	0.164	(0.370)	0.140	(0.348)	
=12	0.320	(0.467)	0.298	(0.458)	
>12 Highest grade completed by father	0.181	(0.385)	0.176	(0.381)	
=12	0.237	(0.425)	0.220	(0.414)	
Living with both parents	0.532	(0.499)	0.510	(0.500)	
Living with single parent	0.241	(0.428)	0.238	(0.426)	
Household size	3.828	(1.535)	3.914	(1.670)	
# of household members at age 6-18	0.635	(0.926)	0.704	(1.025)	
# of household members under age 6	0.148	(0.419)	0.175	(0.465)	
Mother has income (=1 if mother has income)	0.794	(0.404)	0.797	(0.403)	
Father has income (=1 if father has income)	0.867	(0.340)	0.868	(0.339)	
School size	5.255	(0.856)	5.200	(0.880)	
Student-teacher ratio	2.170	(0.754)	2.166	(0.769)	
Living in the northeast	0.172	(0.378)	0.170	(0.376)	
Living in the south	0.353	(0.478)	0.367	(0.482)	
West	0.219	(0.414)	0.231	(0.422)	
MSA	0.825	(0.380)	0.822	(0.383)	
Year 1997	0.005	(0.070)	0.012	(0.108)	**
Year 1998	0.340	(0.474)	0.358	(0.480)	
Year 1999	0.377	(0.485)	0.346	(0.476)	
County unemployment rate	0.043	(0.021)	0.042	(0.019)	

Notes: Standard errors are reported in the parenthesis. There are 2,895 observations. Non-participant sample has 841 and participant sample has 2,054. There are 2,739 observations for compensation, which include 799 non- and 1,939 participants, respectively. Base category for region is North-central; base category for parents' education is <12th grade including no education; base category for race is mixed race/ethic; base category for the relationship to parents is no parents; base category for MSA is lived in urban. Analysis of variance (ANOVA) in the last column indicates that the variations of ethnic indicators "Non-Black and Non-Hispanic" and "black" between two groups are significant. * denotes 10 significance level, ** at 5 percent significance level, and *** at 1 percent significance level.

The third group of variables controls for school-specific factors, which include student-teacher ratio and school size. This group of variables is used to reduce a potential self-selection problem (Neumark and Joyce, 2001).[35] For example, a high student-teacher ratio may impair academic achievements of students because teachers could devote less time to each student and students are more likely to be distracted from classmates (Elliot and Williams, 2000 and Grissmer, et. al. 2000).[36] School administrators or parents may encourage students to participate in school-to-work programs to compensate for their academic loss. In this regard, students in such kinds of schools are more likely to choose a STW program, which causes the participation to be endogenous.

The last group of variables controls for region of residence. Dummy variables are used to indicate the region in which the respondents live and whether the residence is in a Metropolitan Statistical Area (MSA) as of the survey date. The county unemployment rate is included to control for regional labor market conditions (Pabilonia, 2001). The county unemployment rates are obtained from the Bureau of Labor Statistics. In addition, year dummy variables are included such as a dummy variable for 1997, one for 1998, etc. Since students may participate in the school-to-work program in different years, it is

[35] Neumark and Joyce (2001) use school size, student-teacher ratio, school program, school type, and school level to control for unobserved heterogeneity. They provide an example to show that there is a possible correlation between participation and the school-specific variables. For example, if school type is technical or vocational, then the students mainly are high-school-bounded, whose goal is to work after high school graduation rather than to attend college. In this regard, students in such schools are more likely to choose STW program, which cause the participation to be endogenous. However, type of school curriculum is only available in the first round. Therefore, in this paper, only school size and student-teacher ratio are used.

[36] Elliot and Williams (2000) find that high student-teacher ratio causes lower reading abilities of students. Grussmer et. al. (2000) examines scores from the National Assessment of Educational Progress (NAEP) test from 1990-1996 to determine the effect of student/teacher ratio on student test scores. They find that, when other characteristics such as socio-economic status and family background are controlled, higher NAEP test scores are related to lower student-teacher ratio in lower grades.

important to control for time-specific factors, which are related to the macroeconomic environment.

Definitions and descriptive statistics of variables used in the study are presented in Table 2.2.

5. Empirical Specification

This section explains the empirical specification used to analyze the impact of participation in school-to-work programs on wages. A general specification of the human capital earnings function is given by

(5.1) $Y = \alpha + STW\delta + X\beta + \varepsilon$

where

Y	=	wage
STW	=	a dummy variable measuring participation in any STW program
X	=	a vector of individual characteristics
E	=	a random error term,

where δ is the impact of participation in school-to-work program on wages. In order for estimated effects to be unbiased, the error terms must be uncorrelated with the school-to-work program dummy variable. That is, if STW program participation is exogenous to the wage, then ordinary least squares regression of the causal effect of school-to-work program on wages will yield an unbiased estimate of the treatment effect of δ. However, there is a problem known as the non-randomly selected problem in the training literature, which may cause participation in school-to-work programs to be correlated with ϵ. The selection bias may arise from two sources. The first source is the self-selection of

individuals to participate in an activity or survey. For example, individuals with poor academic performance in high school may believe that college is not their best option but instead that work after high school is more appropriate. Therefore, they may self-select themselves into participating school-to-work programs to learn job skills and achieve work experience, which will expedite their transition from school to high-skill or high-wage careers. In this regard, the sample of youths who participate in school-to-work programs is constrained among a group of students with a low intelligence level if academic performance is positively influenced by mental capacity. Consequently, the analysis based on such a sample will under-estimate the causal effect of school-to-work programs. The second source is the selection of samples or studies by administrators or researchers to support a particular hypothesis, which causes potential differences between treatment and control groups. Consider the administrators in those schools offering school-to-work programs. One of the purposes of the school-to-work programs is to provide disadvantaged youths with job training to compensate for weaknesses and gain competitive advantages so that they can transfer from school to stable employment more successfully. If the administrator unilaterally pursues the effectiveness of the program, then they may discriminate against those less capable and discourage them to join STW programs. If so, then there are large differences in observed characteristics of youths between the two groups so that the training effects may be over-estimated.

Because STW program participants are a nonrandom sample of the population, two methods are used to control for selection bias. The first approach is to use Ordinary Least Squares (OLS) with a full set of covariates to control for individual-specific, school-specific, and time-specific factors in ϵ that are potentially correlated with *STW*. Using this

method, the selection bias problem can be reduced by including a large set of covariates to control for unobserved characteristics that might affect employment outcomes.

The second approach to use is the propensity score matching method. This approach is used in the literature, for example, by Heckman, Ichimura, and Todd (1997), Dehejia and Wahba (1998), Hotz, Imbens, and Mortimer (1999), Lechner (1999), and Levine and Painter (2003) to produce unbiased treatment effects.[37] In observational studies, investigators have no control over the assignment of units to the treated or control groups. If there are significant differences in observable characteristics such as ethnicity or age between treated and control groups, then estimated treatment effects will be biased.

Rubin (1977) and Rosenbaum and Rubin (1983) proposed a propensity score method to reduce bias in observational studies. The intuition of the propensity score method is to compare the outcomes of treatment subjects with those of control subjects who have similar observable characteristics. The propensity score is written as

(5.2) $$p(X_i) \equiv P(T_i = 1 | X_i)$$

where $p(X)$ is the propensity score. It refers to the conditional probability of assignment to a particular treatment ($T_i = 1$) versus control ($T_i = 0$) given a vector of observed covariates, X_i. There are two assumptions required in order to identify treatment effects:

Assumption 1: Conditional on X, T and (Y_0, Y_1) are independent.

$$(Y_{i1}, Y_{i0}) \perp T_i | X_i$$

Assumption 2: $0 < pr(T = 1 | X_i) < 1, \forall X$

[37] Dehejia and Wahba (1998) use propensity score methods to estimate the treatment impact of the National Supported Work Demonstration. Their results from the propensity matching methods are very close to the estimate from the experimental results. Levine and Painter (2003) use propensity score matching estimator to examine the effect of teenage out-of-wedlock pregnancy on schooling. Their findings suggest adverse effects of teen childbearing on high school completion are caused by pre-existing disadvantages of the young women not by childbirth itself.

where

Y_{i1} is the outcome if unit i was exposed to the treatment

Y_{i0} is the outcome if unit i was not exposed to the treatment

Rosenbaum and Rubin (1983) call assumption (1) ignorability of treatment (given observed covariates X) and assumption (1) plus (2) strong ignorability of treatment. The treatment effect of a randomly selected individual from the population is

(5.3) $$ATE \equiv E(Y_{i1} - Y_{i0})$$

where ATE is referred by Rosenbaum and Rubin (1983) as the average treatment effect. However, this effect has been criticized as not being relevant for practical use because it includes those who are not actually eligible for the training program (Wooldridge, 2002). For example, Heckman (1997) points out that millionaires should be excluded in computing the average effect of a job-training program because of their outliers' effects. Therefore, the effect of interest is the average treatment effect on the treated (ATT):

(5.4) $$\tau\big|_{T=1} \equiv E(Y_{i1}|T_i = 1) - E(Y_{i0}|T_i = 1) = E(Y_{i1} - Y_{i0}|T_i = 1)$$

where τ is the treatment effect for the treated population. However, Y_{i0} cannot be observed, since $T_i = 1$, which means that the unit is under the treatment and is the only outcome where treatment can be observed. Assumption (1) implies that conditional on observables X, Y_{i1}, and Y_{i0} are independent of treatment status, T. Therefore, the following equation is obtained:

(5.5) $$E(Y_{ij}|X_i, T_i = 1) = E(Y_{ij}|X_i, T_i = 0) = E(Y_i|X_i, T_i = j),\ j = (0, 1).$$

Essentially, when X is partialed out, Y_j is uncorrelated with T even if a correlation does exist. Therefore, the treatment effect of the treated (ATT) can be estimated as follows:

(5.6) $$\tau|_{T=1} \equiv E(Y_{i1} - Y_{i0}|T_i = 1) = E\{E(Y_i|X_i, T_i = 1) - E(Y_i|X_i, T_i = 0)|T_i = 1\}.$$

The following two implications in (5.5) are needed to derive (5.6) given (5.5).

(5.7) $$E(Y_{i1}|T_i = 1) = E(Y_{i1}|X_i, T_i = 1) = E(Y_{i1}|X_i, T_i = 0)$$

(5.8) $$E(Y_{i0}|T_i = 1) = E(Y_{i0}|X_i, T_i = 1) = E(Y_{i0}|X_i, T_i = 0).$$

However, it is infeasible to estimate equation (5.6) with a large number of covariates because of the 'curse of dimensionality'. The propensity score makes it feasible, which reduces large numbers of pre-treatment characteristics of each subject into a single-index variable and conditioning on this index is equivalent to conditioning on X. Therefore, for all X, assumptions (1) and (2) imply

$$\{(Y_{i1}, Y_{i0}) \perp T_i\}|p(X_i)$$

and

$$0 < pr\{T = 1|p(X_i)\} < 1.$$

Estimation of equation (5.6), the average treatment effect of the treated, therefore, can be obtained as follows:

(5.9) $$\tau|_{T=1} \equiv E\{E\{Y_{i1} - Y_{i0}|T_i = 1, p(X_i)\}\}$$

(5.10) $$= E\{E(Y_{i1}|T_i = 1, p(X_i)) - E(Y_{i0}|T_i = 0, p(X_i))|T_i = 1\}.$$

Equation (5.10) implies the distribution of the covariates is the same for observations with the same propensity score.

Implementing the propensity score matching method to get unbiased estimates requires two steps, which are detailed by Dehejia and Wahba (1998). First, the propensity score is estimated using a probit or a logit model.

$$P_r\{T_i = 1|X_i\} = \Phi(h(X_i))$$

where Φ denotes the standard normal density function. For the logistic cumulative distribution function, Φ is replaced with Λ. $h(X_i)$ is a specification that includes the set of covariates. According to Equation (5.10), observations with the same propensity score should have the same distribution of covariates across the treated and controlled groups. To test whether there are significant differences in the distribution of covariates between two groups, the sample is divided into intervals based on the estimated propensity score. If the test shows that the means of each covariate do not differ, then there is no statistically significant difference in the pre-intervention characteristics between groups; thus the specification is accepted. If the test fails for some blocks, then these blocks are divided into narrower blocks and checked for balance again within these finer blocks. If a covariate is not balanced for all blocks, then a more general specification of $h(X_i)$ including higher-order terms and interactions of the covariates is attempted until the balancing hypothesis is satisfied.

The second step is to estimate the average treatment effect using the equation (5.10). Given the estimated propensity score, the stratification matching, the nearest neighbor matching, and the radius matching are used in this paper to obtain the average treatment effect. First, the stratification matching is used. Within each stratum, the mean difference in the wage between the treated and control units is calculated. Then the overall treatment effect is obtained by averaging these differences.

However, there is a disadvantage when using the stratification method because it discards observations when either treated or control units are not matched. Therefore, the nearest neighbor matching method is used to circumvent this problem. Each treated unit is matched with the control unit that has the closest propensity score. Once each treated unit is matched with an untreated unit, the difference between the outcomes of treated observations and the outcomes of the paired unit is computed. The average treatment effect is averaged over all the pairs to get the overall treatment effect. The drawback of the nearest neighbor match is that a treated unit will be paired with an untreated unit even if they have very different propensity scores. Therefore, a matching method that requires the propensity scores between the treated unit and the untreated unit to be close enough is necessary. The Radius Matching method provides such a solution where the difference of propensity scores between the treated unit and the matched controls must fall within a pre-determined radius.

6. Empirical Results

6.1. Descriptive statistics

Tables 2.2 to 2.4 present descriptive statistics for both explanatory variables and outcomes. Table 2.2 compares descriptive statistics for participants and non-participants. Analysis of variance (ANOVA) is used to test whether treated and control units have the same pattern of dispersion by comparing the means of independent variables. If the means of an explanatory variable do not differ significantly, then it is inferred that the independent variable does not have an effect on the dependent variable. Otherwise, it is concluded that the independent variable has an effect on the dependent variable. The *F*-values indicate that most explanatory variables are not significantly different between

participants and non-participants. However, the variations of ethnic indicators "Non-Black and Non-Hispanic (NBNH)", "black," and year dummy variable for 1997 between two groups are significant.

Table 2.3 reports the distribution of school-to-work program participation by gender and ethnicity. First, the participation rate of the full sample in a school-to-work program is more than 70.95 percent. Females have a slightly higher participation rate of 71.28 percent than males' 70.59 percent. The participation rate in school-based learning programs is higher than that in work-based programs. The participation rate in a career major program is the highest of the seven school-to-work programs. Second, non-black and non-Hispanic youths have the highest number of participants, while black youths have the highest participation rate of 75.71 percent.

TABLE 2.3 SCHOOL-TO-WORK PROGRAM PARTICIPATION RATES BY DEMOGRAPHIC CHARACTERISTICS

	Any activities	Work-Based Activities					School-Based Activities				Sample Mean
		Any Work-based	Internship/ apprenticeship	Job Shadowing	Mentoring	School-Education Enterprise	Any School-based	Career Major	Coop-Education	Tech prep	
Gender:											
Male	972	630	230	345	180	193	795	643	310	295	1377
	(70.59)	(45.75)	(16.70)	(25.05)	(13.07)	(14.02)	(57.73)	(46.70)	(22.51)	(21.42)	
Female	1082	768	261	444	236	266	837	712	299	223	1518
	(71.28)	(50.59)	(17.19)	(29.25)	(15.55)	(17.52)	(55.14)	(46.90)	(19.70)	(14.69)	
Ethnicity:											
NBNH	1154	784	263	463	207	242	889	737	319	253	1657
	(69.64)	(47.31)	(15.87)	(27.94)	(12.49)	(14.60)	(53.65)	(44.48)	(19.25)	(15.27)	
Black	508	360	128	191	130	144	436	360	183	159	671
	(75.71)	(53.65)	(19.08)	(28.46)	(19.37)	(21.46)	(64.98)	(53.65)	(27.27)	(23.70)	
Hispanic	372	239	94	124	71	69	291	242	104	103	543
	(68.51)	(44.01)	(17.31)	(22.84)	(13.08)	(12.71)	(53.59)	(44.57)	(19.15)	(18.97)	

Notes: The integer is the number of youths participating in each particular STW program and the number in parenthesis is the corresponding percentage of youths participating in each particular STW program.

Table 2.4 compares the average wage of participants to non-participants by school-to-work program and by gender and ethnicity. First, there is a significant wage gap between male and female participants. Male participants have a higher wage by more than 12 percent ((7.974-7.067)/7.067) than female participants. Second, female work-based school-to-work programs participants have slightly higher wages than female school-based programs participants, while the wage gap is almost the same for male participants. Third, a wage gap exists between participants and non-participants of STW programs. Male participants have a 5.8 percent ((7.974-7.533)/7.533) higher wage than male non-participants, while this gap is smaller by only 1.9 percent for female participants and non-participants. Male internship or apprenticeship programs participants have the highest hourly wage, while female school-sponsored enterprise program participants have the lowest hourly wage. The wage gap between participants and non-participants of internship or apprenticeship is the most significant. Particularly, the wage gap is more than 7.2 percent between male participants and non-participants, while the gap between female participants and non-participants is 4.4 percent. Participants have a higher wage than non-participants for most school-to-work programs. However, there are two exceptions. Female participants in school-sponsored enterprise program and technical preparation program have lower wages than non-participants.

TABLE 2.4 HOURLY RATE OF PAY BY SCHOOL-TO-WORK PROGRAM AND BY DEMOGRAPHIC CHARACTERISTICS

	Any activities	Work-Based Activities					School-Based Activities				Sample Mean
		Any Work-based	Internship/ apprenticeship	Job Shadowing	Mentoring	School-Education Enterprise	Any School-based	Career Major	Coop-Education	Tech prep	
Gender:											
Male	7.974	8.047	8.309	7.944	8.073	8.146	8.046	8.015	8.139	7.943	1377
	(7.533)	(7.674)	(7.751)	(7.811)	(7.810)	(7.795)	(7.569)	(7.695)	(7.759)	(7.817)	
Female	7.067	7.087	7.282	7.110	7.226	6.888	7.038	7.102	7.181	6.924	1518
	(6.933)	(6.968)	(6.975)	(6.994)	(6.992)	(7.058)	(7.016)	(6.963)	(6.991)	(7.046)	
Ethnicity:											
NBNH	7.560	7.561	7.756	7.512	7.636	7.645	7.614	7.619	7.854	7.804	1657
	(7.225)	(7.366)	(7.402)	(7.437)	(7.433)	(7.426)	(7.278)	(7.329)	(7.364)	(7.396)	
Black	7.208	7.248	7.337	7.156	7.397	6.975	7.178	7.102	7.254	7.026	671
	(7.150)	(7.131)	(7.160)	(7.209)	(7.145)	(7.254)	(7.223)	(7.301)	(7.171)	(7.246)	
Hispanic	7.670	7.793	8.293	7.790	7.743	7.422	7.753	7.876	7.714	7.394	543
	(7.279)	(7.354)	(7.391)	(7.475)	(7.517)	(7.565)	(7.308)	(7.282)	(7.507)	(7.583)	

Notes: Average hourly wages for non-participants are reported in parentheses. Average wage for males and females are $7.844 and $7.028 per hour, respectively.

Table 2.4 also reports the wage by school-to-work programs and by ethnicities. First, non-black and non-Hispanic and Hispanic participants have 4.9 percent and 6.4 percent higher wages than the black participants. Second, non-black and non-Hispanic and Hispanic participants have 4.6 percent and 5.4 percent higher hourly wages than NBNH and Hispanic non-participants, while the black participants only earn 0.8 percent more than black non-participants. Third, non-black and non-Hispanic participants have a higher wage than non-participants for all school-to-work programs. However, only internship or apprenticeship, mentoring, and coop-education programs can make black participants earn a higher hourly wage than non-participants. Hispanic participants have lower wages in school-sponsored enterprise and technical preparation programs. Fourth, non-black and non-Hispanic participants of school-based activities earn more than participants of worked-based activities, while black and Hispanic participants of worked-based programs have higher wages than participants of school-based programs.

6.2. Regression results

In this section, the regression results are reported. The basic specification of the earnings function (5.1) is estimated without controlling for personal, family, and school characteristics. The only information controlled in this specification is whether youths participate in any school-to-work program. Since in the earnings specification, the logarithm of wages is used, the coefficients can be interpreted as the proportionate effect of a unit change in the relevant characteristics on wages. First, all school-to-work programs are combined together. If youths participate in any school-to-work programs, then they will be treated as a participant of school-to-work programs. It is expected that participants have a higher wage than non-participants. Then, the participants are divided

into two categories, school-based learning and work-based learning. Finally, these two categories are broken into discrete school-to-work programs. In doing so, it is expected that particular programs have stronger effects on wages. The coefficients and robust standard errors are reported in the Table 2.5. First, the coefficient in the first column shows that school-to-work activities have positive effects on the wage; however, it is not statistically significant. Second, school-based programs have a positive 4.0 percent and statistically significant effect on wage versus non-participants, whereas the effects of the work-based activities are weaker and insignificant. Third, the effects of particular types of school-to-work programs are examined. The results indicate that participants in mentoring activities earn 3.8 percent more than non-participants, while participants of career major, coop-education, and technical preparation make 2.7 percent, 3.7 percent, and 3.0 percent more per hour than non-participants. As expected, some school-to-work programs have stronger effects on wages than others. It is notable that most school-to-work programs have positive effects on the wages, while the school-sponsored enterprise program has a negative effect on wages.

TABLE 2.5 REGRESSION RESULTS OF OLS

	Any activities	Work-Based Activities					School-Based Activities			
		Any Work-based	Internship/ apprenticeship	Job Shadowing	Mentoring	School-Education Enterprise	Any School-based	Career Major	Coop-Education	Tech prep
OLS	0.027	0.017	0.037	0.002	0.038*	-0.017	0.040**	0.027*	0.037*	0.030*
(no controls)	(0.017)	(0.016)	(0.023)	(0.019)	(0.021)	(0.024)	(0.017)	(0.016)	(0.020)	(0.018)
R^2	0.0008	0.0004	0.001	0.0000	0.001	0.0002	0.002	0.001	0.001	0.001
OLS	0.033*	0.024	0.035	0.008	0.039*	-0.0001	0.044***	0.031*	0.046**	0.025
(full controls)	(0.017)	(0.016)	(0.022)	(0.019)	(0.020)	(0.023)	(0.017)	(0.016)	(0.020)	(0.019)
R^2	0.052	0.051	0.051	0.051	0.051	0.051	0.053	0.052	0.052	0.051

Notes: Robust standard errors against heteroscedasticity are reported in parentheses. * significant at 10 percent level; ** at 5 percent level; *** at 1 percent level. Models included missing dummy variables and an intercept.

To control for omitted variables, the OLS models are re-estimated with a full set of independent variables. Results are reported in row 4 of Table 2.5. The R^2 indicates a better fit than the OLS specification without covariates. The results in the first column show that youths participating in school-to-work programs have 3.3 percent higher wages than non-participants. It is notable that the effect becomes statistically significant at the 10 percent level. However, the effect of participation in work-based activities is still not significant although the coefficient is positive. Within the category of work-based learning, participation in mentoring activities still has a positive 3.9 percent effect on wages and is significant at the 10 percent level. There are several exceptions when compared to the estimates of OLS without covariates. The effect of participation in school-based activities on wages increases to 4.4 percent and is significant at the 1 percent level. The magnitudes of effects of participation in career and coop-education programs on wages increase to 3.1 percent and 4.6 percent, respectively. The program of technical preparation loses its significance level, while the effect of the coop-education program increases the significance level to 5 percent.

The coefficients on the other explanatory variables generally conform to the prior expectations (Tables 2.1, 2.2, and 2.3 in Appendix). Males earn an hourly wage by 10 percentage points higher than females. However, youths who residing in the south have lower wages by an approximate 9 percentage points. In addition, the wages are adversely affected by "age", "year 1998", and "the county unemployment rate."

However, OLS estimates could be biased because participants of any school-to-work activities may have self-selected into the program and their participation may be correlated with unobservable characteristics. Therefore, the propensity score matching

method is applied to reduce this bias by controlling for the existence of the confounding factors.

A logit model is used to estimate the propensity score for the participation in school-to-work programs. The logit specification is the same as the OLS specification in that it includes the covariates of personal, family, school, and location characteristics. Figure 2.1 compares the number of treatment and control units within each block defined on the estimated propensity score for the participants and non-participants of school-to-work programs. The figure does not include the control units whose estimated propensity score is less than the minimum or more than the maximum for the treatment units. Figure 2.1 indicates that there are five blocks for the treatment "participate in any school-to-work programs" and within each block there is a good overlap in the estimated propensity score between the treatment and control group. Particularly, in block 1 there are 78 treatment units and 52 untreated units with an estimated propensity score of 0.4. In blocks 2, 3, and 4, there are 698 and 370, 1115 and 383, and 163 and 33 treated and control units with estimated propensity scores of 0.6, 0.7, and 0.8, respectively. This overlap is necessary to guarantee that differences can be found if they exist. Figure 2.2 presents the comparison between the participants and non-participants of school-based activities. There is a significant overlap between the treatment and the control units. Figure 2.3 plots the histogram for the work-based activities participants and non-participants. Overall, for most bins there are sufficient numbers of comparison units.

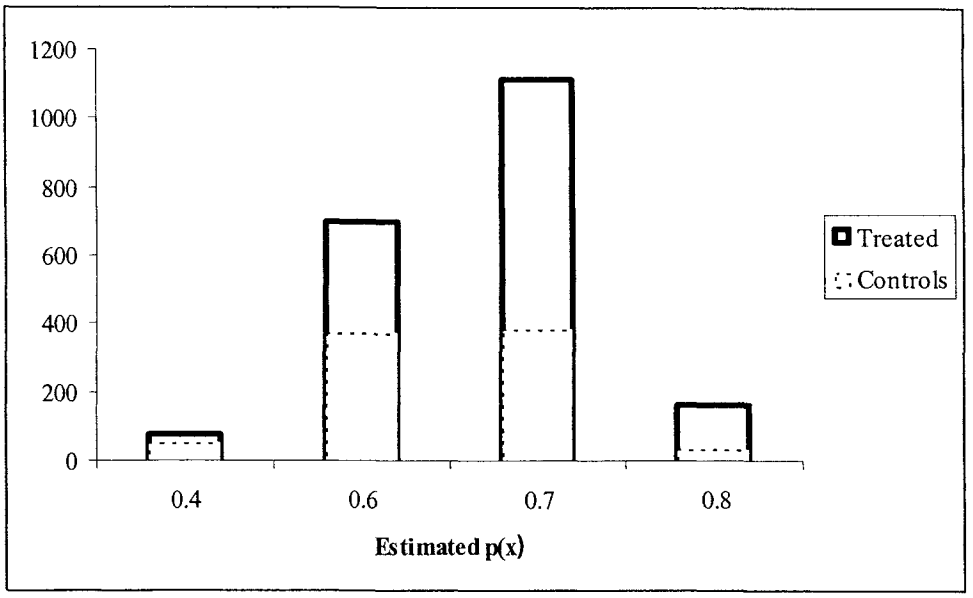

FIGURE 2.1 HISTOGRAM OF THE ESTIMATED PROPENSITY SCORE FOR THE PARTICIPATION IN ANY SCHOOL-TO-WORK PROGRAMS

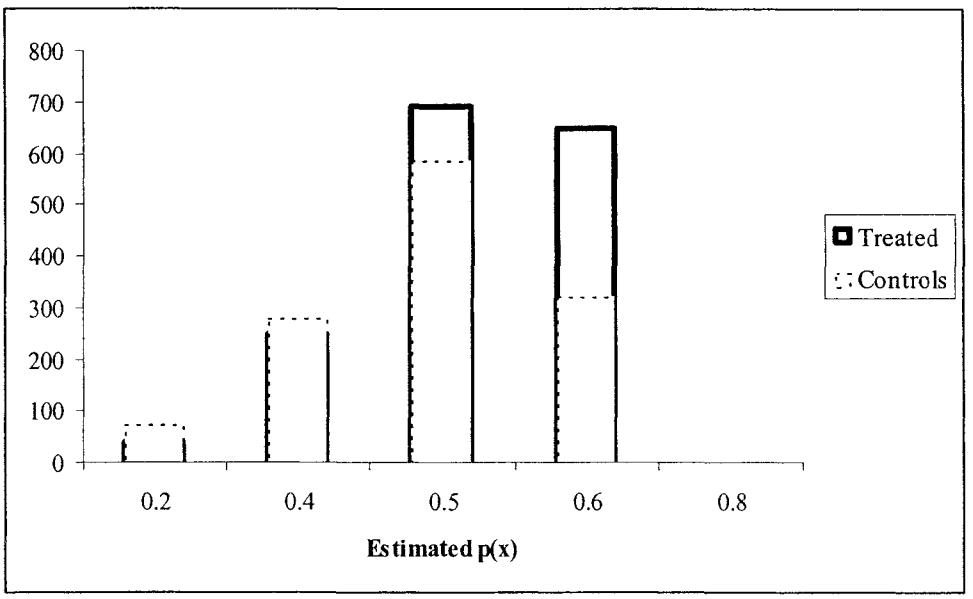

FIGURE 2.2 HISTOGRAM OF THE ESTIMATED PROPENSITY SCORE FOR THE PARTICIPATION IN ANY SCHOOL-BASED SCHOOL-TO-WORK PROGRAMS

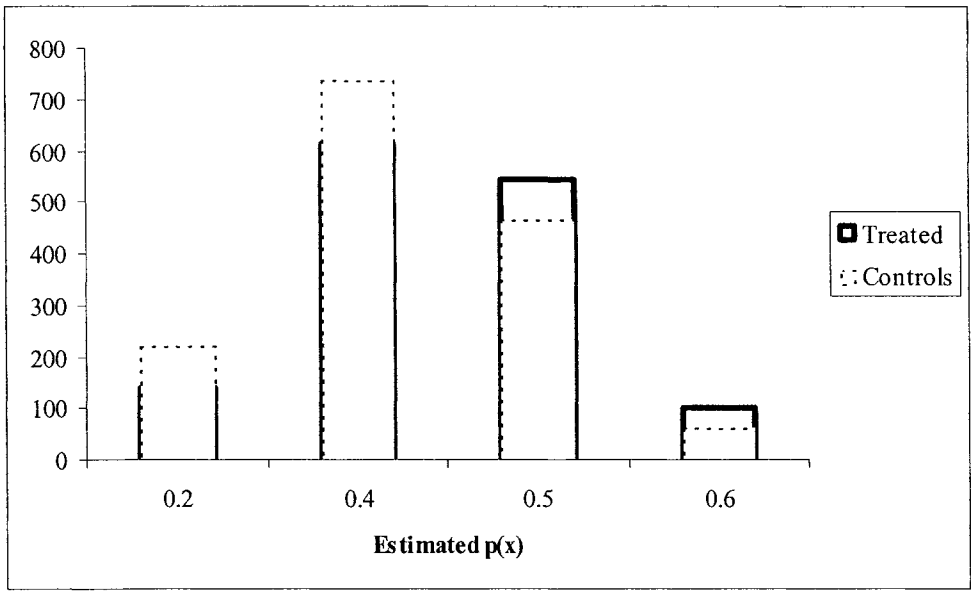

FIGURE 2.3 HISTOGRAM OF THE ESTIMATED PROPENSITY SCORE FOR THE PARTICIPATION IN ANY WORK-BASED SCHOOL-TO-WORK PROGRAMS

Stratification, nearest neighbor matching, and radius matching estimators are used to examine the average treatment effects of participation in school-to-work programs on wages. Table 2.6 reports the propensity score estimates of the effects. First, all school-to-work programs are combined together. The stratification estimator indicates that participation in any school-to-work program significantly raises the hourly wage by 3.2 percent. The nearest neighbor matching method shows a positive effect of 4.6 percent, which is significant at the 10 percent level. The estimates are also statistically significant for the radius matching methods. The effect is 5.8 percent at the 0.0001 (γ<0.0001) level, while the effects are 4.5 and 4.6 percent for both radius methods with γ <0.0005 and γ <0.001. Therefore, participation increases wages by 3.2 to 5.8 percent per hour than non-participation. The magnitudes are larger than those obtained by OLS. Next, school-to-work programs are divided into work-based and school-based activities. In column 2, the

results from stratification and matching estimators indicate that work-based activities have effects similar to OLS in terms of magnitudes, though they are statistically insignificant. However, school-based activities have significantly positive effects on wages. For the stratification estimator, participation increases wages by 4.0 percent. The nearest neighbor matching method gives a smaller 2.9 percent positive effect; however, it is insignificant. For the radius matching methods with $\gamma < 0.0005$ and $\gamma < 0.001$, the magnitudes increase to 5.2 percent and 5.2 percent, respectively, which are consistent with the estimates of OLS with covariates. Finally, the propensity score method is used to examine the effects of particular types of school-to-work programs. Within the category of work-based activities, stratification, nearest neighbor matching, and radius matching estimators consistently indicate that mentoring activity significantly raises wages by 3.9 to 7.7 percentage points per hour, which implies that it is an effective program in preparing the students for first jobs in high-wage careers. The estimates of nearest matching show that internship or apprenticeship activity has a significant positive effect on wages. The magnitude implies that participants have 5.7 percent higher hourly wages than non-participants. However, the estimates of stratification and radius matching do not support that participation in these activities has significantly positive effect on wages. It is notable that participation in school-sponsored enterprise activities has a negative effect on wages for radius matching and stratification methods, respectively, although the magnitudes are very small and insignificant. Within the category of school-based activities, the stratification estimate indicates that cooperative education program participation has a 3.8 percent causal effect on wages, which is significant at 10 percent level. Although the nearest matching estimate does not produce a significant causal effect

of cooperative education participation, it consistently shows a 3.9 percent effect on wages. Three different levels of the radius matching estimators consistently show a positive effect of cooperative education participation on wages. For radius method with $\gamma < 0.0001$, the effect of participation in cooperative education is 7.7 percent, which is significant at 10 percent level. For radius method with $\gamma < 0.0005$ and $\gamma < 0.001$, cooperative education participation significantly increases wages by 4.4 and 4.3 percent, respectively.

TABLE 2.6 PROPENSITY SCORE ESTIMATES OF THE EFFECT OF THE PARTICIPATION ON HOURLY WAGE RATE

	Any activities	Work-Based Activities					School-Based Activities			
		Any Work-based	Internship/ apprenticeship	Job Shadowing	Mentoring	School-Education Enterprise	Any School-based	Career Major	Coop-Education	Tech prep
Stratification	0.032*	0.019	0.032	0.005	0.042**	-0.007	0.040**	0.027	0.038*	0.024
	(0.019)	(0.016)	(0.025)	(0.021)	(0.021)	(0.022)	(0.017)	(0.017)	(0.023)	(0.020)
Matching:										
Nearest Matching	0.046*	0.012	0.057*	0.004	0.077*	0.013	0.029	0.045**	0.039	-0.013
	(0.027)	(0.024)	(0.031)	(0.027)	(0.040)	(0.038)	(0.025)	(0.022)	(0.036)	(0.038)
Radius: δ<0.0001	0.058**	0.045	0.034	0.012	0.039	-0.004	0.017	0.042	0.077*	0.023
	(0.029)	(0.040)	(0.038)	(0.039)	(0.041)	(0.040)	(0.036)	(0.041)	(0.042)	(0.043)
Radius: δ<0.0005	0.045*	0.026	0.041	0.003	0.048*	-0.003	0.052**	0.034	0.044**	0.029
	(0.027)	(0.018)	(0.028)	(0.025)	(0.027)	(0.029)	(0.023)	(0.023)	(0.021)	(0.024)
Radius: δ<0.001	0.046**	0.027	0.037	0.006	0.039*	-0.001	0.052**	0.027	0.043**	0.027
	(0.020)	(0.018)	(0.027)	(0.020)	(0.021)	(0.025)	(0.022)	(0.023)	(0.024)	(0.021)

Notes: Bootstrapping standard errors are reported in the parentheses. * denotes 10 percent significance level, ** at 5 percent significant level, and *** at 1 percent significant level. Propensity scores are estimated using the logit model with the following specification: Pr = F(STW, age, age^2, male, white, black, Hispanic, grade, AFQT, two dummies for household relationship, three dummies for region, MSA, household income, four dummies for parental education,, two dummies indicating whether parents have income, household size, # of children under age 6, # of children between age 6 and 18, school size, student/teacher ratio, unemployment rate, and missing dummy variables).

To determine whether there are gender differences in effects of participation in school-to-work programs, the full sample is divided by gender. Table 2.7 presents the propensity score estimates of the effect. Estimates of stratification method indicate that male participants of any work-based or school-based activities earn more than 6 percentage points than male non-participants per hour, while female participants of any school-to-work activities have a higher hourly wage by 3.9 percent than female non-participants. However, the estimates of nearest matching and radius matching do not suggest that there are significant gender differences on the effects of participation of school-to-work activities because results are insignificant at 10 percent level.

Overall, stratification and matching methods yield estimates that are consistent in terms of direction and magnitude with those of OLS with a full set of covariates. The fact that similar results obtain from different econometric techniques supports that participation in school-to-work programs has a significantly positive effect ranging from 3.2 percent to 5.8 percent on wages. School-based learning, especially cooperative education program, makes youths earn 3.8 to 7.7 percent more per hour. However, the effects of participation on wages are weaker and insignificant for work-based activities except for the mentoring program.

TABLE 2.7 PROPENSITY SCORE ESTIMATES OF THE EFFECT OF THE PARTICIPATION ON HOURLY WAGE S BY GENDER

	Male			Female		
	Any Activities	Any Work-Based Activities	Any School-Based Activities	Any Activities	Any Work-Based Activities	Any School-Based Activities
Stratification	0.019	0.063**	0.065**	0.039*	0.026	0.019
	(0.022)	(0.027)	(0.025)	(0.023)	(0.021)	(0.025)
Matching:						
Nearest Matching	0.034	0.006	0.001	0.050	0.032	0.023
	(0.034)	(0.037)	(0.036)	(0.035)	(0.029)	(0.034)
Radius: δ<0.0001	0.020	0.045	0.079	0.116	0.024	0.024
	(0.073)	(0.084)	(0.093)	(0.089)	(0.062)	(0.074)
Radius: δ<0.0005	0.034	0.019	0.039	0.028	0.035	0.035
	(0.035)	(0.040)	(0.040)	(0.043)	(0.035)	(0.029)
Radius: δ<0.001	0.032	0.013	0.039	0.039	0.026	0.026
	(0.030)	(0.035)	(0.037)	(0.031)	(0.026)	(0.028)

Notes: Bootstrapping standard errors are reported in the parentheses. * denotes 10 percent significance level, ** at 5 percent significant level, and *** at 1 percent significant level. Propensity score are estimated using the logit model with the following specification: Pr = F(STW, age, age^2, white, black, Hispanic, grade, AFQT, two dummies for household relationship, three dummies for region, MSA, household income, four dummies for parental education,, two dummies indicating whether parents have income, household size, # of children under age 6, # of children between age 6 and 18, school size, student/teacher ratio, unemployment rate, and missing dummy variables).

7. Conclusion

School-to-work programs are designed to facilitate the transfer of high school students to a career by providing hands-on experience in a professional work environment. However, there has been little academic work on their effectiveness. This paper seeks to fill this gap by analyzing the effects of participation in the school-to-work program on the hourly wage in the first primary job immediately after high school graduation.

The results from the OLS specification without covariates suggest that participation in any school-to-work programs does positively affect wages of youths, but the estimate is statistically insignificant. When the program is divided into school-based and work-based activities, the estimates show that participation in school-based programs increase youths' wages by 4.0 percent. Within the category of school-based activities, participation in career major, coop-education, and tech preparation programs have statistically significant positive effects on wages. Within the category of work-based programs, only participation in the mentoring activities has any statistically significant effect; it increases wages of youths by 3.8 percent.

However, the estimates from the basic model may be biased due to omitted variables and self-selection. If participation in school-to-work programs is not exogenous, then OLS estimates will be biased. Results from OLS with a full set of pre-intervention variables included largely confirm the findings derived from simple OLS estimates. There are two exceptions. First, participation in any school-to-work program increases wages by a statistically significant 3.3 percent. Second, within the category of school-based activities, only career and coop-education programs significantly affect wages positively, whereas tech prep activities become statistically insignificant. The estimates

also show that the magnitudes of the impacts are slightly larger than those of the basic OLS specification.

If treatment and control groups are dissimilar in pre-treatment characteristics, then it is difficult to estimate the effect of school-to-work programs because of observable characteristics not controlled for in OLS above. The propensity score matching method provides a way to control the differences of pre-intervention variables between treatment and control units. The results estimated by stratification, nearest neighbor matching, and radius matching methods reinforce that (1) participation in the school-to-work programs has a positive effect ranging from 3.2 percent to 5.8 percent on wages; (2) school-based programs are more efficient in increasing the hourly wage than work-based activities because the estimates are not only more significant but also they have larger magnitudes; (3) the effects of particular types of STW program on wages are not equal. In particular, the coop-education and mentoring activities are the most effective raising the wage by 3.8 to 7.7 and 3.9 to 7.7 percentage points per hour, respectively. These findings are useful for policy makers because they support the development and implementation of school-to-work programs. On the other hand, some of the school-to-work programs do not affect wages; therefore, the limited funds could be relocated to focus exclusively on those programs that are effective.

REFERENCES

1. Altonji, Koseph G. and Thomas A. Dunn. 1996. "The Effects of Family Characteristics on the Return to Education." *Review of Economics and Statistics*, 78(4): 692-704.
2. Ashenfelter, Orley. 1978. "Estimating the Effect of Training Programs on Earnings." *Review of Economics and Statistics*, 60(1): 47-57.
3. Ashenfelter, Orley and David Card. 1985. "Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs." *Review of Economics and Statistics*, 67(4): 648-660.
4. Ashenfelter, Orley and David J. Zimmerman. 1993. "Estimates of the Returns to Schooling from Sibling Data: Fathers, Sons, and Brothers." *Working Paper No. 4491*, National Bureau of Economic Research.
5. Bassi, Laurie J. 1984. "Estimating the Effect of Training Programs with Non-Random Selection." *Review of Economics and Statistics*, 66(1): 36-43.
6. Baum, Charles L. 2003. "Does Early Maternal Employment Harm Child Development? An Analysis of the Potential Benefits of Leave Taking." *Journal of Labor Economics*, 21(2): 409-448.
7. Baum, Charles L. and William F. Ford. 2004. "The Wage Effects of Obesity: A Longitudinal Study." *Forthcoming* in *Health Economics*.
8. Becker, Sascha O. and Andrea Ichino. 2002. "Estimating of Average Treatment Effects Based on Propensity Scores." *Stata Journal*, 2(4): 358-377.
9. Beyer, J. De and Knight John B. 1989. "The Role of Occupation in the Determination of Wages." *Oxford Economic Papers*, 41(3): 595-618.
10. Brazil, Jeff. 1999. "Play Dough." *American Demographics*, December, 57-61.
11. Carr, Rhoda V., James D. Wright, and Charles J. Brody. 1996. "Effects of High School Work Experience a Decade Later: Evidence from the National Longitudinal Survey." *Sociology of Education*, 69: 66-81.
12. Committee on the Health and Safety Implications of Child Labor. 1998. "Protecting Youth at Work: Health, Safety and Development of Working Children and Adolescents in the United States." Edited by the Board on Children, Youth, and Families Commission on Behavioral and Social Sciences and Education (National Research Council), Institute of Medicine. Washington D.C.: National Academy Press.
13. Dehejia, R. and Wahba S. 1998. "Propensity Score Matching Methods for Non-Experimental Causal Studies." NBER Working Paper 6586, National Bureau of Economic Research, Inc.
14. Dorfman, John. 1982. "Did Inflation Whip You?" *Forbes*, April 26, 129: 96.
15. Dustmann, Christian and John Micklewright. 2001. "Intra-Household Transfers and the Part-Time Work of Children." *Working Paper*, University College London.
16. Ghosh, Koushik. 1999. "Does Early Work Experience Matter?" *Journal of Economics*, 25(1): 61-83.
17. Goldfarb, Robert S. and Anthony M. J. Yezer. 1983. "A Model of Teenage Labor Supply." *Journal of Economics and Business*, 35: 245-255.

18. Greenberger Ellen and Laurence Steinberg. 1986. *When Teenagers Work: The Psychological and Social Costs of Adolescent Employment*, New York: Basic Books, Inc.
19. Greene, William H. 2003. *Econometric Analysis*, 5th Edition, New Jersey: Pearson Education, Inc.
20. Grissmer, David, Ann Flanagan, Jennifer Kawata, and Stephanie Williamson. 2000. *Improving Student Achievement: What State NAEP Test Scores Tell Us*, Santa Monica, CA: RAND.
21. Hausman, Jerry A. 1978. "Specification Tests in Econometrics." *Econometrica*, 46(6): 1251-71.
22. Heckman, James. 1997. "Instrumental Variables: A Study of Implicit Behavioral Assumptions in One Widely Used Estimator." *Journal of Human Resources*, 32(3): 441-462.
23. Heckman, James, H. Ichimura, and P. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program." *Review of Economic Studies*, 64(4): 261-294.
24. Heckman, James J. and Thomas E. MaCurdy. 1986. "Labor Econometrics." *Handbook of Econometrics*, edited by Z. Griliches, Volume 3: 1917-1977, Amsterdam: North-Holland.
25. Heckman, James J., Robert J. LaLonde, and Jeffrey A. Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." *Handbook of Labor Economics*, edited by Orley Ashenfelter and David Card, Volume 3: 1865-2097, Amsterdam: North-Holland.
26. Hershey, Alan M., Marsha K. Silverberg, and Joshua Haimson. 1999. *Expanding Options for Students: Report to Congress on the National Evaluation of School-to-Work Implementation*, Princeton, New Jersey: Mathematica Policy Research, Inc.
27. Holtz-Eakin, Douglas, Joulfaian David, and Rosen, Harvey. 1993. "The Carnegie Conjecture: Some Empirical Evidence." *Quarterly Journal of Economics*, 108(2): 413-435.
28. Hotz, V. Joseph, Guido W. Imbens, and Julie H. Mortimer. 1999. "Predicting the Efficacy of Future Training Programs Using Past Experiences." NBER Technical Working Papers 0238, National Bureau of Economic Research, Inc.
29. Huang, Lynn, Michael Pergamit, and Jamie Shkolnik. 2001. "Youth Initiation into the Labor Market." *Monthly Labor Review*, August, 18-24.
30. Jakubson, George. 1988. "The Sensitivity of Labor-Supply Parameter Estimates to Unobserved Individual Effects: Fixed- and Random-Effects Estimates in a Nonlinear Model Using Panel Data." *Journal of Labor Economics*, 6(3): 302-329.
31. Johnston, L., J. Bachman, and P. O'Malley. 1982. "Monitoring the Future: Questionnaire Responses from the Nation's High School Seniors, 1981." Institute for Social Research, University of Michigan, Ann Arbor.
32. Joice, Mary and David Neumark. 2001. "School-to-Work Programs: Information from Two Surveys." *Monthly Labor Review*, August, 38-50.
33. Kaestner, Robert. 1991. "The Effect of Illicit Drug Use on the Wages of Young Adults." *Journal of Labor Economics*, 9(4): 381-412.

34. Kelly, Katy. 2000. "Making Allowances for Your Kids' Dollar Values." *U. S. News & World Report*, February, 63.
35. Kilburn, M. Rebecca, Lawrence M. Hanser, and Jacob Alex Klerman. *Estimating AFQT scores for National Educational Longitudinal Study (NELS) Respondents*, United States Department of Defense Office of the Secretary of Defense, Rand Corporation, National Defense Research Institute.
36. Korenman, Sanders and David Neumark. 1992. "Marriage, Motherhood and Wages." *Journal of Human Resources*, 27(2): 233-255.
37. Lancaster, T. 2000. "The incidental parameters problem since 1948." *Journal of Econometrics*, 95: 391-414.
38. Lechner, Michael. 1999. "Earnings and Employment Effects of Continuous Off-the-Job Training in East Germany after Unification," *Journal of Business and Economic Statistics*, 17(1): 74-90.
39. Levine, David and Gary Painter. 2003. "The Schooling Costs of Teenage Out-of-Wedlock Childbearing: Analysis with a Within-School Propensity-Score-Matching Estimator." *Review of Economics and Statistics*, 85(4): 884-900.
40. Lewis, Diane E. July 11, 1999. "In Tight Job Market, Shops Looking to Younger Teens." Globe Newspaper Company: G1.
41. Light, Audrey. 1999. "High School Employment, High School Curriculum, and Post-School Wages." *Economics of Education Review*, 18(3): 291-309.
42. Loury, Linda D. and Glenn C. Loury. 1983. "The Effects of Attitudes and Aspirations on the Labor Supply of Young Black Men." Cambridge MA, *Conference on Inner City Black Youth Unemployment.*
43. Lundberg, Shelly and Elaina Rose. 2002. "The Effects of Sons and Daughters on Men's Labor Supply and Wages." *Review of Economics and Statistics*, 84 (2): 251-268.
44. Marsh, Herbert W. 1991. "Employment during High School: Character Building or a Subversion of Academic Goals?" *Sociology of Education*, 64: 172-189.
45. Michael, Robert T. and Nancy Brandon Tuma. 1984. "Youth Employment: Does Life Begin at 16?" *Journal of Labor Economics*, 2(4): 464-476.
46. Micklewright, John and Dustmann Christian. 1994. "Labouring and Learning: Part-Time Work and Full-Time Education." *National Institute Economic Review*, May, 73-85.
47. Miller, Joanne and Susan Yung. 1990. "The Role of Allowances in Adolescent Socialization." *Youth and Society*, 22(2): 137-159.
48. Mortimer, Jeylan T. and Monic Kirkpatrick Johnson. 1998. "New Perspectives on Adolescent Work and the Transition to Adulthood." *New Perspective on Adolescent Risk Behavior*, Edited by R. Jesser, New York: Cambridge University Press.
49. Neumark, David. 2001. "Evaluating School-to-Work Programs Using the New NLSY." *Journal of Human Resources*, 36(4): 667-702.
50. Neumark, David. 2002. "Youth Labor Markets in the U.S.: Shopping Around vs. Staying Put." *Review of Economics and Statistics*, 84(3): 462-482.
51. Neyman, J. and E. Scott. 1948. "Consistent estimates based on partially consistent observations." *Econometrica,* 16: 1-32.

52. Orazem, Peter F. and J. Peter Mattila. 1986. "Occupational Entry and Uncertainty: Males Leaving High School." *Review of Economics and Statistics*, 68(2): 265-273.
53. Pabilonia, Sabrina Wulff. 2001. "Evidence on Youth Employment, Earnings, and Parental Transfers in the National Longitudinal Survey of Youth 1997." *Journal of Human Resources,* 36(4): 795-822.
54. Pencavel, John. 1986. "A Labor Supply of Men: A Survey." *Handbook of Labor Economics*, Edited by Ashenfelter, O. and Layard P.R.G., Vol.1, Amsterdam: North Holland.
55. Ree, A. and W. Gray. 1982. "Family Effects in Youth Employment." *The Youth Labor Market Problem*, edited by R. B. Freeman and D. A. Wise, Chicago: University of Chicago Press.
56. Riggio, Ronald E. and Heidi R. Riggio. 1999. *Evaluation of School-to-Work Programs Using the NLSY97 Database*, Kravis Leadership Institute, Claremont McKenna College.
57. Robertson, D. and J. Symons, 1990. "The Occupational Choice of British Children." *Economic Journal*, 100: 828-841.
58. Rosenbaum, P. R. and Rubin D. B. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika*, 70: 41-45.
59. Rothstein, Donna S. 2001. "Youth Employment in the United States." *Monthly Labor Review*, August, 8-17.
60. Rubin, D. B. 1977. "Assignment to Treatment Group on the Basis of a Covariate." *Journal of Educational Statistics*, 2: 1-26.
61. Ruhm, Christopher J. 1997. "Is High School Employment Consumption or Investment?" *Journal of Labor Economics*, 15(4): 735-776.
62. Schill, William J., Rosemarie McCartin, and Katrina Meyer. 1985. "Youth Employment: Its Relationship to Academic and Family Variables." *Journal of Vocational Behavior*, 26: 155-165.
63. Stern, David, Neal Finkelstein, James R. Stone, John Latting, and Carolyn Dornsife. 1994. *Research on School-to-Work Transition Programs in the United States*, Berkeley, CA: National Center for Research in Vocational Education, University of California.
64. Stone III, James R. 2002. "The Impact of School-to-Work and Career and Technical Education in the United States: Evidence from the National Longitudinal Survey of Youth, 1997." *Journal of Vocational Education and Training*, 54(4): 553-578.
65. Tapales, Athena. 2001. "Work and Adolescence in the United States: Understanding the Role of Work among High School Students and Dropouts." Johns Hopkins School of Hygiene & Public Health.
66. U.S. Department of Education, National Center for Education Statistics. 1996. "Youth Indicators." NCES96-027, by Tomas Snyder and Linda Shafer. Washington, D. C.
67. U.S. Department of Labor. Bureau of Labor Statistics. 2000. "Report on the Youth Labor Force." by Alexis M. Herman, Washington, D. C.
68. U.S. Department of Labor. Bureau of Labor Statistics. 2002. *NLSY97 User's Guide,* Columbus, Ohio: Center for Human Resource Research.

69. Vuri, Daniela. 2002. "Propensity Score Estimates of the Effect of Fertility on Marital Dissolution." Working Paper, European University Institute.
70. Waldfogel, Jane.1997. "The Effects of Children on Women's Wages." *American Sociological Review*, 62: 209-217.
71. Wolpin, Kenneth I. 1992. "The Determinants of Black-White Differences in Early Employment Careers: Search, Layoffs, Quits and Endogenous Wage Growth." *Journal of Political Economy*, 100(3): 535-560.
72. Wooldridge, Jeffrey M. 2001. *Econometric Analysis of Cross Section and Panel Data*, Cambridge: MIT press.
73. Yeatts, James. 1994. "Which Students Work and Why?" Master's thesis, Greensboro: University of North Carolina.
74. Zarkin, Gary A., Thomas A. Mroz, Jeremy W. Bray, and Michael T. French. 1998. "The Relationship between Drug Use and Labor Supply for Young Men." *Labor Economics*, 5(4): 385-409.

APPENDIX

TABLE 1.1 RESULTS OF OLS ESTIMATION

Variable	Model (1) OLS		Model (2) OLS		Model (3) OLS with Covariates	
Continuous Allowance	-65.498†	(6.971)	—	—	—	—
Low allowance	—	—	-133.85	(5.46)	-66.627†	(5.242)
Medium Allowance	—	—	-109.83	(7.41)	-68.690†	(6.958)
High allowance	—	—	-73.46	(8.43)	-74.443†	(7.895)
Age	—	—	—	—	89.891†	(2.009)
Male	—	—	—	—	42.665†	(4.946)
Black	—	—	—	—	25.156	(22.318)
NBNH	—	—	—	—	68.296†	(21.958)
Hispanic	—	—	—	—	29.143	22.470)
Grade	—	—	—	—	-1.092	(1.251)
Height	—	—	—	—	0.657	(0.628)
AFQT	—	—	—	—	5.415‡	(2.374)
No household income	—	—	—	—	-20.161‡	(8.658)
Low Household income	—	—	—	—	5.334	(12.508)
Middle household income	—	—	—	—	-6.392	(12.258)
High household income	—	—	—	—	10.641	(13.335)
Mother completed high school	—	—	—	—	7.927	(6.021)
Mother completed college	—	—	—	—	-14.893	(7.254)
Father completed high school	—	—	—	—	5.958	(5.789)
Father completed college	—	—	—	—	-0.976‡	(7.471)
Have both parents	—	—	—	—	-2.539	(9.559)
Have single parent	—	—	—	—	-14.987	(9.737)
Siblings# between age 6 & 18	—	—	—	—	-6.963†	(1.936)
Siblings# under age 6	—	—	—	—	5.413	(4.711)
Mother has income	—	—	—	—	-32.780	(6.057)
Father has income	—	—	—	—	1.472†	(5.367)
South	—	—	—	—	-45.743†	(5.782)
North-east	—	—	—	—	-33.954†	(6.774)
West	—	—	—	—	-38.984†	(6.667)
MSA	—	—	—	—	-9.793±	(5.580)
County unemployment rate	—	—	—	—	-0.518†	(0.094)
R^2		0.004		0.031		0.164

Notes: There are 22,506 person-year observations. Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 1.2 RESULTS OF FIXED EFFECTS MODELS ESTIMATION

Variable	Model (4) Individual Fixed Effects		Model (5) Siblings Fixed Effects		Model (6) Individual Differenced Sibling Effects	
Low allowance	-45.195†	(5.532)	-39.385†	(8.770)	-30.787‡	(15.702)
Medium Allowance	-69.450†	(7.451)	-59.252†	(12.290)	-64.012†	(26.525)
High allowance	-73.162†	(7.895)	-78.678†	(15.347)	-78.449†	(33.358)
Age	106.958†	(2.432)	105.729†	(3.489)	110.781†	(5.045)
Male	—	—	56.790†	(10.583)	51.262†	(12.095)
Black	—	—	-118.341	(138.753)	-87.068	(152.573)
NBNH	—	—	-46.179	(124.336)	2.225	(140.874)
Hispanic	—	—	-80.341	(132.638)	9.660	(150.247)
Grade	-0.729	(1.256)	-0.167	(2.010)	-3.627	(3.027)
Height	-5.684†	(1.016)	-3.281‡	(1.294)	-3.307‡	(1.689)
AFQT	—	—	22.239†	(5.772)	20.142†	(6.950)
No household income	-44.412†	(9.169)	-39.219†	(14.986)	-34.668	(46.043)
Low Household income	34.859†	(12.745)	14.979	(21.576)	-67.554	(87.235)
Middle household income	-18.355	(12.715)	-24.927	(21.607)	-100.970	(89.027)
High household income	-1.879	(13.754)	-8.005	(23.772)	97.914	(105.320)
Mother completed high school	—	—	-34.506	(60.506)	-57.979	(67.694)
Mother completed college	—	—	-88.000	(89.763)	-29.398	(101.341)
Father completed high school	—	—	158.746‡	(65.305)	139.046±	(73.750)
Father completed college	—	—	25.924	(81.773)	37.181	(93.922)
Have both parents	18.700	(15.958)	0.042	(22.406)	-3.913	(39.226)
Have single parent	-3.497	(15.401)	-28.359	(22.106)	-20.686	(40.716)
Siblings# between age 6 & 18	-20.209†	(3.233)	-15.394†	(4.615)	-27.580‡	(12.524)
Siblings# under age 6	-5.739	(6.579)	-9.447	(10.911)	-92.403‡	(40.694)
Mother has income	-32.316†	(6.729)	-41.562†	(10.601)	-38.460‡	(17.587)
Father has income	-53.668†	(6.810)	-38.172†	(10.844)	-80.256†	(17.381)
South	-32.481	(32.447)	-26.339	(61.873)	-401.040†	(148.365)
North-east	-12.769	(51.303)	-12.405	(99.501)	33.608	(236.468)
West	-31.100	(37.692)	101.653	(66.010)	-176.103	(173.053)
MSA	6.190	(21.357)	51.172	(33.677)	294.858†	(93.991)
County unemployment rate	-0.223‡	(0.104)	-0.397‡	(0.176)	-0.150	(1.747)
Number of Observations		22,506		9,263		9,263
R^2		0.134		0.118		0.054

Notes: Robust Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 1.3 RESULTS OF RANDOM EFFECTS MODELS ESTIMATION

Variable	Full Sample		Siblings Sample	
Low allowance	-56.574†	(5.090)	-49.430†	(8.552)
Medium Allowance	-71.413†	(6.684)	-59.058†	(11.482)
High allowance	-78.052†	(7.613)	-78.275†	(13.995)
Age	99.640†	(1.984)	100.119†	(3.164)
Male	53.361†	(6.979)	48.353†	(8.653)
Black	23.945	(33.551)	5.023	(47.434)
NBNH	72.537‡	(33.033)	66.316	(46.476)
Hispanic	20.768	(33.747)	6.694	(47.713)
Grade	-1.104	(1.137)	-0.303	(1.912)
Height	-1.634‡	(0.731)	-0.640	(1.075)
AFQT	8.106‡	(3.459)	11.191†	(4.269)
No household income	-34.640†	(7.961)	-31.049‡	(13.512)
Low Household income	20.731±	(11.283)	18.412	(19.802)
Middle household income	-10.180	(11.175)	-10.632	(19.659)
High household income	5.251	(12.103)	7.588	(21.610)
Mother completed high school	9.368	(8.630)	0.373	(13.354)
Mother completed college	3.634	(11.217)	-22.304	(17.169)
Father completed high school	14.137	(9.045)	19.964	(13.895)
Father completed college	-10.850	(10.861)	-12.127	(16.670)
Have both parents	5.535	(11.053)	-8.348	(17.149)
Have single parent	-14.279	(11.074)	-24.089	(17.398)
Number of siblings between age 6 & 18	-12.986†	(2.236)	-8.050‡	(3.473)
Number of siblings under 6	0.600	(5.023)	1.550	(8.478)
Mother has income	-15.517†	(5.470)	-18.731‡	(8.999)
Father has income	-48.636†	(5.811)	-40.998†	(9.786)
South	-51.560†	(8.379)	-44.968†	(12.917)
North-east	-42.304†	(9.920)	-35.317‡	(15.224)
West	-45.894†	(9.633)	-19.887	(14.982)
MSA	-6.870	(7.860)	-2.511	(12.135)
County unemployment rate	-0.352†	(0.091)	-0.464†	(0.152)
Number of Observations		22,506		9,263
R^2		0.161		0.164
Prob>Chi^2		0.000		0.000
$Chi^2(25)$		192.99		111.31

Notes: Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 1.4 RESULTS OF PROBIT MODELS ESTIMATION

Variable	Probit		Probit		Probit with Covariates	
Allowance	-0.226†	(0.027)	—	—	—	—
Low allowance	—	—	-0.628†	(0.023)	-0.340†	(0.026)
Medium Allowance	—	—	-0.428†	(0.030)	-0.252†	(0.034)
High allowance	—	—	-0.233†	(0.033)	-0.286†	(0.036)
Age	—	—	—	—	0.523†	(0.010)
Male	—	—	—	—	0.101†	(0.025)
Black	—	—	—	—	0.158	(0.109)
NBNH	—	—	—	—	0.374†	(0.107)
Hispanic	—	—	—	—	0.142	(0.110)
Grade	—	—	—	—	-0.008	(0.006)
Height	—	—	—	—	0.017†	(0.003)
AFQT	—	—	—	—	0.065†	(0.011)
No household income	—	—	—	—	0.052	(0.044)
Low Household income	—	—	—	—	-0.001	(0.066)
Middle household income	—	—	—	—	-0.042	(0.064)
High household income	—	—	—	—	-0.040	(0.069)
Mother completed high school	—	—	—	—	-0.026	(0.027)
Mother completed college	—	—	—	—	0.032	(0.035)
Father completed high school	—	—	—	—	0.047±	(0.028)
Father completed college	—	—	—	—	0.033	(0.034)
Have both parents	—	—	—	—	-0.093‡	(0.045)
Have single parent	—	—	—	—	-0.119†	(0.046)
Siblings# between age 6 & 18	—	—	—	—	0.003	(0.009)
Siblings# under age 6	—	—	—	—	0.003	(0.024)
Mother has income	—	—	—	—	0.190†	(0.024)
Father has income	—	—	—	—	0.113†	(0.029)
South	—	—	—	—	-0.253†	(0.027)
North-east	—	—	—	—	-0.029	(0.032)
West	—	—	—	—	-0.133†	(0.031)
MSA	—	—	—	—	0.012	(0.026)
County unemployment rate	—	—	—	—	-0.003†	(0.000)
Log-likelihood	-14126.042		-13722.712		-10746.853	

Notes: There are 22,506 person-year observations. Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 1.5 RESULTS OF FIXED EFFECTS LOGIT MODELS ESTIMATION

Variable	Full Sample		Siblings Sample	
Low allowance	-0.312†	(0.103)	-0.586†	(0.109)
Medium Allowance	-0.187	(0.127)	-0.511†	(0.137)
High allowance	-0.529†	(0.137)	-0.522†	(0.158)
Age	1.654†	(0.046)	1.262†	(0.042)
Male	—	—	0.400†	(0.117)
Black	—	—	0.279	(1.271)
NBNH	—	—	0.490	(1.184)
Hispanic	—	—	0.239	(1.273)
Grade	0.0002	(0.020)	-0.002	(0.021)
Height	-0.002	(0.023)	0.012	(0.015)
AFQT			0.120	(0.059)
No household income	-0.507†	(0.164)	-0.103	(0.171)
Low Household income	0.466±	(0.241)	0.094	(0.238)
Middle household income	0.113	(0.245)	0.032	(0.235)
High household income	-0.092	(0.268)	-0.187	(0.259)
Mother completed high school	—	—	-0.180	(0.572)
Mother completed college	—	—	-0.425	(0.856)
Father completed high school	—	—	1.749†	(0.606)
Father completed college	—	—	-0.214	(0.750)
Have both parents	0.321	(0.281)	-0.176	(0.253)
Have single parent	0.341	(0.270)	-0.261	(0.248)
Number of siblings between age 6 & 18	0.116‡	(0.058)	-0.025	(0.049)
Number of siblings under age 6	0.078	(0.127)	-0.084	(0.121)
Mother has income	0.428†	(0.120)	0.175	(0.122)
Father has income	0.416†	(0.120)	0.313	(0.126)
South	-0.324	(0.602)	0.001	(0.683)
North-east	-3.329†	(1.124)	-0.915	(1.266)
West	-0.136	(0.737)	0.040	(0.683)
MSA	-0.637	(0.390)	0.615	(0.327)
County unemployment rate	-0.003	(0.002)	-0.004	(0.002)
Number of Observations		12,327		7,523
log-likelihood		-1840.346		-1777.222

Notes: Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 1.6 RESULTS OF RANDOM EFFECTS PROBIT MODELS ESTIMATION

Variable	Full Sample		Siblings Sample	
Low allowance	-0.659†	(0.032)	-0.686†	(0.051)
Medium Allowance	-0.568†	(0.041)	-0.527†	(0.065)
High allowance	-0.371†	(0.044)	-0.357†	(0.076)
Age	—	—	—	—
Male	0.232†	(0.029)	0.256†	(0.046)
Black	0.224	(0.157)	0.343	(0.239)
NBNH	0.333‡	(0.154)	0.482‡	(0.234)
Hispanic	0.115	(0.158)	0.190	(0.240)
Grade	-0.008	(0.007)	-0.006	(0.011)
Height	—	—	—	—
AFQT	0.148†	(0.016)	0.178†	(0.025)
No household income	0.245†	(0.050)	0.250†	(0.078)
Low Household income	0.121	(0.074)	0.145	(0.115)
Middle household income	-0.047	(0.073)	0.061	(0.114)
High household income	-0.045	(0.078)	0.067	(0.123)
Mother completed high school	-0.081‡	(0.039)	-0.187†	(0.065)
Mother completed college	-0.005	(0.051)	-0.098	(0.082)
Father completed high school	0.015	(0.041)	0.059	(0.067)
Father completed college	0.010	(0.049)	0.054	(0.080)
Have both parents	-0.315†	(0.059)	-0.298†	(0.092)
Have single parent	-0.279†	(0.060)	-0.287†	(0.094)
Number of siblings between age 6 & 18	-0.177†	(0.012)	-0.197†	(0.019)
Number of siblings under age 6	-0.019	(0.030)	0.062	(0.045)
Mother has income	0.509†	(0.031)	0.442†	(0.048)
Father has income	0.642†	(0.034)	0.641†	(0.053)
South	-0.290†	(0.039)	-0.233†	(0.062)
North-east	-0.081±	(0.045)	0.048	(0.072)
West	-0.183†	(0.045)	0.023	(0.072)
MSA	0.022	(0.038)	0.016	(0.059)
County unemployment rate	0.000	(0.001)	0.000	(0.001)
Number of Observations		22,506		9,263
log-likelihood		-11,962.811		-4908.7807
$Chi^2(23)$		674.03		273.40
$Prob>Chi^2$		0.0000		0.0000

Notes: Standard errors are in parentheses. ± significant at 10 percent level; ‡ at 5 percent level; † at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 2.1 OLS ESTIMATION RESULTS ON THE CONTROL VARIABLES BY ANY SCHOOL-TO-WORK PROGRAM

	(1) Any Activities		(2) Work-based Activities		(3) School-based Activities	
Participation in (1), (2), or (3)	0.033*	(0.017)	0.024	(0.016)	0.044***	(0.017)
Age	-0.630*	(0.342)	-0.633*	(0.341)	-0.617*	(0.341)
Age^2	0.018*	(0.010)	0.018*	(0.010)	0.017*	(0.010)
Male	0.108***	(0.017)	0.109***	(0.017)	0.107***	(0.017)
White	-0.044	(0.076)	-0.045	(0.076)	-0.043	(0.075)
Black	-0.035	(0.077)	-0.035	(0.077)	-0.036	(0.076)
Hispanic	-0.001	(0.076)	-0.001	(0.077)	0.001	(0.075)
GPA in 8^{th} grade	0.007	(0.007)	0.007	(0.007)	0.008	(0.007)
AFQT	0.006	(0.009)	0.006	(0.009)	0.006	(0.009)
Living with both parents	0.018	(0.026)	0.019	(0.025)	0.017	(0.025)
Living with single parent	0.001	(0.029)	0.002	(0.029)	0.001	(0.029)
Living in the west	0.032	(0.027)	0.031	(0.027)	0.033	(0.027)
Living in the south	-0.090***	(0.020)	-0.090***	(0.020)	-0.089***	(0.020)
Living in the northeast	-0.003	(0.024)	-0.003	(0.024)	-0.004	(0.024)
MSA	0.015	(0.023)	0.016	(0.023)	0.015	(0.023)
Gross household income	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Mother w/ college or higher degree	-0.048	(0.030)	-0.048	(0.030)	-0.046	(0.030)
Mother w/ high school degree	-0.038*	(0.023)	-0.037	(0.023)	-0.038	(0.023)
Father w/ college or higher degree	0.022	(0.028)	0.022	(0.028)	0.022	(0.028)
Father w/ high school degree	0.030	(0.026)	0.030	(0.026)	0.030	(0.026)
Father has income	-0.027	(0.022)	-0.028	(0.022)	-0.027	(0.022)
Mother has income	0.022	(0.023)	0.022	(0.023)	0.022	(0.023)
Household size	-0.012	(0.009)	-0.012	(0.009)	-0.011	(0.008)
# of household members under age 6	0.014	(0.024)	0.014	(0.024)	0.015	(0.023)
# of household members at age 6-18	0.012	(0.011)	0.012	(0.011)	0.012	(0.011)
School size	-0.002	(0.010)	-0.002	(0.010)	-0.004	(0.010)
Student-teacher ratio	0.014	(0.010)	0.014	(0.010)	0.014	(0.010)
Year 1997	-0.092	(0.078)	-0.100	(0.078)	-0.091	(0.079)
Year 1998	-0.049**	(0.022)	-0.049**	(0.022)	-0.050**	(0.022)
Year 1999	-0.031	(0.021)	-0.031	(0.021)	-0.032	(0.022)
County unemployment rate	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
R^2	0.052		0.051		0.053	

Notes: Robust standard errors are in parentheses. * significant at 10 percent level; ** at 5 percent level; *** at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 2.2 OLS ESTIMATION RESULTS ON THE CONTROL VARIABLES BY SCHOOL-BASED ACTIVITIES

	Career Major		Coop Education		Tech Prep	
Participation in School-based Activities	0.031*	0.016	0.046**	0.020	0.025	0.019
Age	-0.625*	0.341	-0.632*	0.344	-0.639*	0.342
Age^2	0.018*	0.010	0.018*	0.010	0.018*	0.010
Male	0.108***	0.017	0.107***	0.017	0.106***	0.017
White	-0.042	0.075	-0.051	0.075	-0.050	0.075
Black	-0.033	0.077	-0.041	0.076	-0.039	0.077
Hispanic	0.001	0.076	-0.007	0.075	-0.007	0.076
GPA in 8^{th} grade	0.007	0.007	0.008	0.007	0.008	0.007
AFQT	0.006	0.009	0.006	0.009	0.006	0.009
Living with both parents	0.019	0.025	0.019	0.025	0.019	0.025
Living with a single parent	0.002	0.029	-0.001	0.029	0.002	0.029
Living in the west	0.033	0.027	0.033	0.027	0.032	0.027
Living in the south	-0.089***	0.020	-0.091***	0.020	-0.091***	0.020
Living in the northeast	-0.004	0.024	-0.004	0.024	-0.004	0.024
MSA	0.015	0.023	0.014	0.023	0.015	0.023
Gross household income	0.000	0.000	0.000	0.000	0.000	0.000
Mother with a college or a higher degree	-0.047	0.030	-0.047	0.030	-0.045	0.030
Mother w/ a high school degree	-0.038	0.023	-0.037	0.023	-0.037	0.023
Father with a college or a higher degree	0.023	0.028	0.023	0.028	0.022	0.028
Father w/ a high school degree	0.031	0.026	0.031	0.026	0.031	0.026
Father has income	-0.026	0.023	-0.029	0.022	-0.027	0.022
Mother has income	0.022	0.023	0.022	0.023	0.022	0.023
Household size	-0.012	0.009	-0.012	0.009	-0.012	0.009
# of household members under age 6	0.014	0.024	0.015	0.024	0.013	0.024
# of household members at age 6-18	0.012	0.011	0.011	0.011	0.012	0.011
School size	-0.003	0.010	-0.003	0.010	-0.002	0.010
Student-teacher ratio	0.013	0.010	0.014	0.010	0.013	0.010
Year 1997	-0.094	0.079	-0.091	0.079	-0.100	0.079
Year 1998	-0.050**	0.022	-0.049**	0.022	-0.049**	0.022
Year 1999	-0.031	0.022	-0.032	0.022	-0.030	0.021
County unemployment rate	-0.002***	0.000	-0.002***	0.000	-0.002***	0.000
R^2	0.052		0.052		0.051	

Notes: Robust standard errors are in parentheses. * significant at 10 percent level; ** at 5 percent level; *** at 1 percent level. Models included missing dummy variables and an intercept.

TABLE 2.3 OLS ESTIMATION RESULTS ON THE CONTROL VARIABLES BY WORKED-BASED ACTIVITIES

	Internship/ Apprenticeship		Job Shadowing		Mentoring		School-Enterprise Enterprise	
Participation in Work-based Activities	0.035	(0.022)	0.008	(0.019)	0.039*	(0.020)	-0.0001	(0.023)
Age	-0.620*	(0.341)	-0.636*	(0.342)	-0.635*	(0.342)	-0.636*	(0.342)
Age^2	0.017*	(0.010)	0.018*	(0.010)	0.018*	(0.010)	0.018*	(0.010)
Male	0.108***	(0.017)	0.108***	(0.017)	0.109***	(0.017)	0.108*	(0.017)
White	-0.045	(0.075)	-0.047	(0.076)	-0.040	(0.075)	-0.049	(0.076)
Black	-0.034	(0.077)	-0.035	(0.077)	-0.031	(0.077)	-0.036	(0.077)
Hispanic	-0.002	(0.076)	-0.004	(0.076)	0.003	(0.076)	-0.005	(0.076)
GPA in 8^{th} grade	0.007	(0.007)	0.008	(0.007)	0.007	(0.007)	0.008	(0.007)
AFQT	0.006	(0.009)	0.006	(0.009)	0.006	(0.009)	0.006	(0.009)
Living with both parents	0.019	(0.025)	0.020	(0.025)	0.019	(0.025)	0.020	(0.025)
Living with a single parent	0.002	(0.029)	0.002	(0.029)	0.002	(0.029)	0.002	(0.029)
Living in the west	0.031	(0.027)	0.031	(0.028)	0.030	(0.027)	0.031	(0.027)
Living in the south	-0.091***	(0.020)	-0.091***	(0.020)	-0.090***	(0.020)	-0.091*	(0.020)
Living in the northeast	-0.004	(0.024)	-0.003	(0.025)	-0.005	(0.024)	-0.004	(0.024)
MSA	0.015	(0.023)	0.016	(0.023)	0.016	(0.023)	0.015	(0.023)
Gross household income	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Mother with a college or a higher degree	-0.047	(0.030)	-0.046	(0.030)	-0.047	(0.030)	-0.046	(0.030)
Mother with a high school degree	-0.036	(0.023)	-0.037	(0.023)	-0.038	(0.023)	-0.037	(0.023)
Father with a college or a higher degree	0.022	(0.028)	0.022	(0.028)	0.022	(0.028)	0.022	(0.029)
Father with a high school degree	0.030	(0.026)	0.031	(0.026)	0.030	(0.026)	0.031	(0.026)
Father has income	-0.027	(0.022)	-0.027	(0.022)	-0.027	(0.022)	-0.027	(0.022)
Mother has income	0.021	(0.024)	0.022	(0.023)	0.021	(0.023)	0.022	(0.023)
Household size	-0.012	(0.009)	-0.012	(0.009)	-0.012	(0.009)	-0.012	(0.009)
# of household members under age 6	0.013	(0.024)	0.013	(0.024)	0.014	(0.024)	0.013	(0.024)
# of household members at age 6-18	0.012	(0.011)	0.012	(0.011)	0.012	(0.011)	0.012	(0.011)
School size	-0.002	(0.010)	-0.002	(0.010)	-0.001	(0.010)	-0.002	(0.010)
Student-teacher ratio	0.014	(0.010)	0.013	(0.010)	0.013	(0.010)	0.013	(0.010)
Year 1997	-0.102	(0.079)	-0.100	(0.079)	-0.097	(0.079)	-0.101	(0.079)
Year 1998	-0.050**	(0.022)	-0.049**	(0.022)	-0.049**	(0.022)	-0.049*	(0.022)
Year 1999	-0.031	(0.021)	-0.030	(0.021)	-0.031	(0.021)	-0.030	(0.021)
County unemployment rate	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
R^2	0.051		0.051		0.051		0.051	

Notes: Robust standard errors are in parentheses. * significant at 10 percent level; ** at 5 percent level; *** at 1 percent level. Models included missing dummy variables and an intercept.