Discussion Paper

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Student Financial Aid, In-School Employment, and Educational and Labor Market Outcomes

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by

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Ever since the Reagan administration assumed office in 1981, tax reductions and decreased government expenditures have been two of the major pillars of the economic policy direction that has come to be known as Reaganomics. The pursuit of this policy orientation has produced an enormous impact on the economy as a whole.

Among policies already implemented, budget cuts in education have fueled much controversy. For example, reductions in student financial aid programs have led some observers to fear that the chances of many needy students to complete their higher education may be adversely influenced because they may have to devote larger blocks of time to part-time work to finance their education. If this occurs, a cut in student aid may adversely affect students' futrue earnings. However, others argue that the student financial aid cuts, may by forcing students to gain labor-market experience, actually increase their future earnings. Due to the ambiguity of the net effect of these two forces, and also due to the fact that cuts in federal student financial aid have occurred and may occur again in the future, it is now relevant to evaluate what the final result of such budget cuts will be and how they will affect the work time decisions, the academic success, and the post-college earnings of students as a whole.

This study is designed to furnish the answers to these questions by evaluating the impact of college students' in-school work experience on their post-college earnings and on their study persistence, respectively. Having estimated the impact of these two, the net impact of in-school work on post-college earnings can be evaluated, and the net effect of cuts in student financial aid can be assessed accordingly.

In the next two sections of the paper, we briefly introduce a simple theoretical model and an empirical model to evaluate the net impact of college students' in-school work on their post-college success. Section III presents the model and the empirical results for the impact of students' in-school work on study persistence. A discussion and some conclusions are presented in section IV by evaluating the net impact of cuts in student financial aid on students' post-college earnings.

1. Related Research and A Simple Theoretical Model

Many studies have focused on the youth employment problem among college students. They have addressed questions such as the effect of students' part-time work on their academic achievements and their study persistence. For example, in their research Apostal and Doherty [1972], Kaiser and Bergen [1968], Merrit [1970], and Trueblood [1957] have all concluded that part-time employment does not adversely affect college students' grade point averages. Similarly, Astin [1975] found that on-campus employment did encourage study persistence. He found that having an on-campus job, particularly during the freshman year, would significantly increase the chances of a student finishing college. However, working at an off-campus job, both during the freshman year and at other points during the student career, was negatively associated with persistence. He also found that working more than twenty-five hours per week had a negative effect on persistence.

Although these studies have focused on the relations between part-time employment and the academic achievements and study persistence of college students, they are not fully satisfactory for two reasons. First, there are some methodological deficiencies. The most common method used to evaluate the effect of part-time jobs on student academic achievements is to separate college students into two groups. A control group and a treatment group. Students in the control group are students who did not work, while students in the treatment group are those who took part-time jobs. Then students in the control group are matched, student-for-student, with students in the treatment group. Researchers claim that through this careful matching students are equated by sex, high school test scores, and college semester hours completed. Finally, simple pairwise t tests, χ^2 tests, or simple correlation measures are employed to find the difference in outcomes between these two groups.

The problem with these two-group-comparison studies is that there is a sample selection bias problem that may not be corrected through these methods. There is only very limited control for the heterogeneity problem. Individual differences in behavior may not be fully captured through simple matching of sex, high school GPA, and college semester hours completed. Other factors that affect a student's behavior such as race, marital status, family income, and family background are typically not controlled for.

Moreover, none of these studies has examined the impact of part-time employment on the post-college success of graduates. Studies on youth unemployment, however, have concentrated on the long-term effects of early spells of teenage unemployment. For example, Stenenson [1978], Ellwood [1982], and Corcoran [1982] have all concluded that early unemployment was associated with lower earnings in subsequent years for all categories of youth. In particular, Meyer and Wise's [1982] study found that there existed a strong relationship between hours of work in high school and weeks worked upon graduation for students not going to college. People who worked while studying in high school also received higher hourly wages than those who did not. It would be interesting to see, given the difference between the nature of high school and college education, whether the labor market experience of college students also has had a singificant impact on their post-college earnings.

To answer questions such as how do college students' work of nonwork time activities affect academic success and post-college wages, or how do financial aid packages affect students' work-time decisions and post-college earnings, one may consider the following simple family utility function:

(1) $U = U[C, Q, t_n, W_p]$

where C: parents' consumption; Q: quality of school the student attends; t_n: nonemployment time of student and W_p: post-college wages. The parents' consumption is given by

(2) $C = Y - X_p$,

where Y is parent's income, and X_p is parental contribution to the student's college expenses. Suppose that the expense, E, a student incurs at any given college is positively related to the quality of the college, that is, that $E = E(Q)$, where $E'(Q) > 0$. Then the total expense of college education can be expressed as

(3) $X_p + X_s + S = E(Q)$.

Here, X_s represents a student's income during college, and S represents scholarships or other types of financial aid received by the student. Now X_s can be explicitly expressed as

(4) $X_s = t_w * W$

and

(5) $T = t_w + t_n$

where t_w is the student's work time, and W is the wage rate he or she faces. Finally, we assume that

(6) $W_p = f(Q, t_n)$.

Equation (6) states that a student's post-college earnings, W_p, are a function of the quality of the school the student attends, Q, and the amount of nonwork time the student enjoys, t_n. It is reasonable to assume that the student's post-college earnings are positively related to the quality of school attended, that is, $\partial W_p/\partial Q > 0$. The effect of t_n on W_p is less obvious. We may assume that some labor market experience will be beneficial to the college student; as the student devotes more of his time to in-school employment, however, additional work time may eventually adversely affect his or her studies and chances of completing the degree program. The time that students devote to labor market activity will therefore have a diminishing marginal return on post-college earnings, which may eventually turn negative, and the relationship between W_p and t_n may be concave from below.

The problem is now to maximize the utility function of (1) subject to constraints (2) through (6). By substituting Equations (2) and (6) into (1), and (4), (5) into (3), we have

Maximize

$$U[Y-X_p, Q, t_n, W_p(Q,t_n)]$$

Subject to

$$X_p + W^*(T-t_n) + S = E(Q).$$

One can totally differentiate the system of first-order conditions and solve to obtain comparative static results. Unfortunately, in this general case, the signs of many of these results remain ambiguous since the functional forms of the utility function, the post-college wage function, and the college cost function are not sufficiently restricted. We will therefore consider an example with several more restrictive assumptions to demonstrate how implications can be drawn concerning how changes in Y, S, and W will affect X_p, Q, and t_n.

To obtain unambiguous results, let us assume the family utility function is a Cobb-Douglas one:

$$U = \alpha_0 (Y - X_p)^{\alpha_1} Q^{\alpha_2} t_n^{\alpha_3} W_p^{\alpha_4}$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4 > 0$ and $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$

and that the post-college wage function is given by[1]

$$W_p = \beta_0 Q^{\beta_1} t_n^{\beta_2} t_n^{-\beta_3}$$

where β_1, β_2, and $\beta_3 > 0$

Notice that concavity in the t_n-W_p function can be obtained if and only if $\beta_2 - \beta_3 > 0$. Since

$$\frac{\partial W_p}{\partial t_n} = \beta_0 Q^{\beta_1} \underset{+}{(\beta_2 - \beta_3)} t_n^{(\beta_2 - \beta_3 - 1)} > 0$$

and

$$\frac{\partial^2 W_p}{\partial t_n^2} = \beta_0 Q^{\beta_1} \underset{+}{(\beta_2 - \beta_3)} \underset{-}{(\beta_2 - \beta_3 - 1)} t_n^{(\beta_2 - \beta_3 - 2)} < 0$$

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1. The purpose of including both β_2 and $-\beta_3$ in the W_p equation is to capture both the positive and negative impacts of t_n on W_p. In-school work experience initially has positive effect on earnings, but the positive effect diminishes as a student devotes more and more to in-school employment. It would, of course, be more desirable to model the t_n-W_p function in a form which allows the marginal effect of the work time to change sign as the number of hours worked varies. For example

$$W_p = \beta_0 Q^{\beta_1} t_n^{\beta_2} (T - t_n)^{\beta_3}$$

However, due to algebraic complications such specifications are not easily solved, and I have used the simpler form for expository convenience.

in that case.

Now let $r_0 = \alpha_0\beta_0^{\alpha_4}$, $r_2 = \alpha_2 + \beta_1\alpha_4$, $r_3 = \alpha_3 + \alpha_4(\beta_2-\beta_3)$, and further assuming that $E(Q) = \delta_0 + \delta_1 Q$, that college costs are a linear function of quality, the Lagrangian function becomes

$$L = [r_0(Y-X_p)^{\alpha_1} Q^{r_2} t_n^{r_3}] + \lambda[X_p+W(T-t_n)+S-\delta_0-\delta_1 Q]$$

One can solve these equations explicitly to obtain the equilibrium solutions:

(7) $$X_p = \left(\frac{\alpha_1}{\alpha_1+r_2+r_3}\right)(\delta_0-S-WT) + \left(\frac{r_2+r_3}{\alpha_1+r_2+r_3}\right)Y$$

(8) $$Q = \frac{r_2}{\delta_1(\alpha_1+r_2+r_3)}(Y-\delta_0+S+WT)$$

(9) $$t_n = \frac{r_3}{W(\alpha_1+r_2+r_3)}(Y-\delta_0+S+WT)$$

Now consider some special cases of this model:

<case 1> if $\alpha_i > 0 \ \forall i$, $\sum_i \alpha_i = 1$, $\sum_j \beta_j = 1$, and $\beta_2 > \beta_3$.

In this case we are assuming that the student's nonwork time, t_n, has a positive but diminishing marginal effect on the student's post-college earnings. Under these assumptions, we find that an increase in family income will increase the parents' contribution, $\frac{\partial X_p}{\partial Y} > 0$, will improve the quality of education, $\frac{\partial Q}{\partial Y} > 0$, and will reduce the student's hours of employment, $\frac{\partial t_n}{\partial Y} > 0$. Similarly, an increase in the financial aid offered will reduce the parent's contribution towards the student's education, $\frac{\partial X_p}{\partial S} < 0$, will enable the student to attend a higher quality school, $\frac{\partial Q}{\partial S} > 0$, and will reduce the student's hours of employment, $\frac{\partial t_n}{\partial S} > 0$. Furthermore, an increase in the student's in-school wage will reduce the parents' educational contribution, $\frac{\partial X_p}{\partial W} < 0$, and make it possible for the student to attend a higher quality college, $\frac{\partial Q}{\partial W} > 0$. The change in the student's wages will not unambiguously affect his hours of employment because both an income and a substitution effect are present, i.e., $\frac{\partial t_n}{\partial W} \gtrless 0$.

From the solution to the model and the post-college wage equation, we can also illustrate directly how the student's family income, the student's scholarship, and the in-school wage affect the post-college wage.

$$\frac{\partial W_p}{\partial Y} = \underset{+}{\frac{\partial W_p}{\partial Q}} \cdot \underset{+}{\frac{\partial Q}{\partial Y}} + \underset{+}{\frac{\partial W_p}{\partial t_n}} \cdot \underset{+}{\frac{\partial t_n}{\partial Y}} > 0.$$

similarly

$$\frac{\partial W_p}{\partial S} > 0, \text{ and } \frac{\partial W_p}{\partial W} = \underset{+}{\frac{\partial W_p}{\partial Q}} \cdot \underset{+}{\frac{\partial Q}{\partial W}} + \underset{+}{\frac{\partial W_p}{\partial t_n}} \cdot \underset{\pm}{\frac{\partial t_n}{\partial W}} \gtreqless 0.$$

In this model a student's family income has a positive effect on future earnings. This is because higher family income allows the student to attend a higher quality institution and to work less while in school. In addition, the financial aid that the student receives also positively influences the student's future earnings, again, for the same two reasons. A cut in student financial aid or loans may inevitably reduce, or even eliminate, low-income students' chances of pursuing a higher quality of education and increase their in-school work effect. Both of these forces will adversely affect their future earnings.

I should stress that the argument about the positive effect of student financial aid on future earnings may not be true in general. So far I have assumed that students' nonwork time, t_n, has a net positive effect on post-college earnings. I now consider the case where an increase in nonwork time has a net negative effect on post-college earnings.

<case 2> If $\alpha_i > 0 \ \forall i$, $\sum_i \alpha_i = 1$, $\sum_j \beta_j = 1$, $\beta_2 - \beta_3 < 0$.

In case 2 a student's part-time employment is assumed to have a net positive effect on post-college earnings so that the net weights of t_n on W_p become negative. That is, $\beta_2 - \beta_3 < 0$, $\partial w_p/\partial t_n < 0$, and $\partial^2 W_p/\partial t_n^2 > 0$. Under this assumption the effects of all of the variables on parental contributions and college quality are the same as before. However, an increase in family income, in student financial aid, or in student wages will not necessarily induce the student to work less due to the presence of both income and substitution effects.

As far as student financial aid is concerned, it may have a positive effect on a student's future earnings if the net effect of S on t_n is nonpositive, since in that case

$$\frac{\partial W_p}{\partial S} = \underset{-}{\frac{\partial W_p}{\partial t_n}} \cdot \underset{-}{\frac{\partial t_n}{\partial S}} + \underset{+}{\frac{\partial W_p}{\partial Q}} \cdot \underset{+}{\frac{\partial Q}{\partial S}} > 0$$

However, it the net effect of S on t_n is positive, then, it is indeterminant as to whether the net effect of an increase in S is to increase W_p. Similarly a student's family income and part-time employment wages will not unabiguously have positive effects on the student's post-college earnings.

The net impact of student financial aid, family income, and part-time wages on post-college earnings cannot be determined conclusively, however, in the theoretical model where t_n has a net negative effect on post-college earnings. It is not possible to make any policy evaluation at the theoretical level as to the net effect of in-school employment on post-college earnings. I will therefore go a step further and address empirical questions such as how cuts in student financial aid affect students' work-time decisions and study persistence, and hence their subsequent earnings. Such an effort is the subject of the net two sections.

2. The Empirical Model

2.1 The Model

In the theorectical model the following system of equations were obtained:

(10) $X_p = f(Y, S, W)$

(11) $Q = f(Y, S, W)$

(12) $t_n = f(Y, S, W)$

(13) $W_p = f(Q, t_n)$

If we consider the above equations as a model for estimation, then Equations (10)-(13) form a recursive system. Moreover, if one substitutes Equation (11) into Equation (13), one obtains[2]

(14) $t_n = f(Y, S, W)$

(15) $W_p = f(Y, S, W, t_n)$.

Notice that Equations (15) and (14) are really the model's post-college wage and in-school employment equations. An econometric model for these two equations, as suggested by the work of Ellwood [1982], can be specified as

(16) $LnW_{ij} = X_{ij}\beta_j + \sum_{t=1}^{4} \alpha_{it}WH_{it} + G_j\lambda_{ij} + \varepsilon_{ij} \qquad j = 1, 3, 5$

(17) $WH_{it} = X_{it}\beta_t + A_{t-1}WH_{it-1} + D_t LnW_{it} + E_t\delta_{it} + C_t\Psi_{it} + U_{it} \qquad t = 1, 2, 3, 4$

where LnW_{ij}: natural log of wages of individual i at the start of post-college year j; X_{ij}: vector of exogenous variables; WH_{it}: total working hours for individual i at college year t; hence $t < j$; λ_{ij}: individual's ability in wage equation; δ_{it}: individual's ease of finding a job; Ψ_{it}: dummy variable to

2. Since the data I use there have no information on parental contributions to education, X_p, I will ignore equation 10 in what follows.

caputre an individual's employment state at the beginning of college year t; and variables A_{t-1}, β_j, β_t, C_t, D_t, α_t, G_j: the coefficients to be estimated. Equation (16), the post-college wage equation, simply states that an individual's wages are a function of a set of exogenous variables, X_{ij}, past labor-market experience, WH_{it}, and ability, λ_{it}. The employment equation states that an individual's total in-school working hours are a function of X_{it}, his wages while in-school, LnW_{it}, his working hours in the previous period, WH_{it}, his ability, δ_{it}, and his employment state at the beginning of period t, Ψ_{it}.

The variables δ_{it} and Ψ_{it} in the employment equation are designed to capture two types of Markovian persistence: the individual's ability to escape from one state to the other, δ_{it}, and his work attachment, Ψ_{it}. The reason why one's ability matters is obvious. An individual's state at the beginning of the period is included to capture his work attachment effect. Once an individual is in a state (say working), it will always be easier for him to stay in that state (remain working) than to get out of it (not working). Therefore, it is reasonable to expect that people who have a job at the beginning of a period are likely to have longer working hours than those who do not have a job initially. Variables δ_{it} and Ψ_{it} respresent two different kinds of heterogeneity, and they capture two types of Markovian persistence.

The easiest way to estimate Equations (16) and (17) is to derive the reduced form of the two equations by assuming $\lambda_{it} = \lambda_i$, $\delta_{it} = \delta_i$, and $\Psi_{it} = \Psi_i$, i.e., to assume all heterogeneity parameters are invariant across time.[3] We

3. Two qualifications are important here. First, since I am using annual data, the importance of Ψ_{it} may be reduced. Second, since the employment statuses of some individuals at the start of each period may change over the four years of college, assuming $\Psi_{it} = \Psi_i$ in the theoretical model may not be strictly valid.

can then condition variable WH in the first year. By continuous substitution, we obtain

(18) $$LnW_{ij} = X_{ij}\beta_j + \sum_{t=2}^{4} X_{it}P_t + Q_1WH_{i1} + \sum_{t=2}^{4} LnW_{it}R_t + S_t\delta_i + \sum_{t=2}^{4} \Psi_i T_t + V\lambda_i + \sum_{t=2}^{4} F_t U_t + \varepsilon_{ij}$$

where β_j, P_t, Q_1, R_t, S_t, T_t, V, and F_t are coefficients to be estimated.

However, as pointed out by Ellwood, there are two problems in this formulation. First, the early experience variable, WH_{i1} may be correlated with an individual's ability, λ, and thus bias the estimates of Q_1 and the bias may become larger as we consider wages further into the future. Second early experience is correlated with both work attachment, Ψ_i, and ease of finding a job, δ_i; this will bias the estimates of Q_1. Estimation of the effect of early labor-market experience, WH_{i1}, on LnW_{ij} may therefore be severely biased.

In addition to the potential problems in the estimates of the reduced form Equations (16) and (17), there is a more fundamental correlation problem. The problem is that Equations (16) and (17) are really two equations of a recursive model, and not all the right-hand-side variables are necessarily truly exogenous. If the in-college employment variable is endogenous in the post-college wage equation, then it may be correlated with the error terms in that equation which would lead to biased parameter estimates. A way to test the independence between the stochastic regressors and the disturbances is suggested by WU [1973, 1974].[4] Hence, before I do any estimation of the actual model I use the WU tests to determine if the disturbances between the two equations are correlated. If they are not, then I proceed to estimate the two equations separately. If the disturbances are correlated, then special estimation methods are used that can estimate this model consistently.

Generally speaking, there are two ways to surmount the problem of correlated disturbances in this model. The first method is to use a variant of two-stage least squares. The estimation proceeds in steps as follows:

First, if it is assumed $\delta_{it} = d_t\delta_i$, and $\Psi_{it} = d_t\Psi_i$, that is, the rates of change of an individual's ability δ_i and employment attachment Ψ_i are steady (or even a constant such as $d_t = 1$), then Equation (17) becomes

(19) $$WH_{it} = X_{it}\beta_t + A_t WH_{it-1} + D_t LnW_{it} + E_t d_t \delta_i + d_t \Psi_i C_t + U_{it}$$

so

(20) $$\delta_i = -\frac{C_t}{E_t}\Psi_i + \frac{1}{E_t d_t}(WH_{it} - X_{it}\beta_t - A_t WH_{it-1} - D_t LnW_{it} - U_{it})$$

Lagging Equation (20) by one period and then substituting it into (19) gives

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4. Professor Nicholas Kiefer has shown that the WU test is equivalent to a Lagrange multiplier test for independence between disturbances and stochastic regressors. The test procedures can be simplified by including both WH_{it} and estimated WH_{it} in the wage equation, and then by seeing which one is significant. If the WH_{it} is significant while the estimated WH_{it} is not, then the WU test suggests no correlation between the stochastic regressors and error terms in the model. If, however, the estimated WH_{it} is significant while the WH_{it} is not, then the existence of a correlation between the error terms and the stochastic regressors is suggested.

$$(21) \qquad WH_{it} = \frac{d_t(C_tE_{t-1}-E_tC_{t-1})\Psi_i}{E_{t-1}} + (A_t + \frac{1}{E_{t-1}d_{t-1}})WH_{it-1} - \frac{A_{t-1}}{E_{t-1}d_{t-1}} WH_{it-2}$$

$$+ X_{it}\beta_t - \frac{\beta_{t-1}}{E_{t-1}d_{t-1}} X_{it-1} + D_t LnW_{it-1} - \frac{D_{t-1}A_{t-1}}{E_{t-1}d_{t-1}} LnW_{it-1} + U_t$$

$$- \frac{1}{E_{t-1}d_{t-1}} U_{it-1}$$

Second, after we have eliminated the ability variable, δ_i, the first stage of estimation is to estimate Equation (21). Estimates of WH_{i3} and WH_{i4} can then be used in the following equation in order to estimate the effects of WH_{it} on LnW_{ij}, i.e.,

$$(22) \qquad LnW_{ij} = X_{ij}\beta_j + \sum_{t=2}^{4} \alpha_{it}\hat{WH}_{it} + G_j\lambda_{ij} + \varepsilon_{ij} \qquad j = 1, 3, 5$$

The advantage of using the instrumental variable is that one eliminates the correlation between WH_{it} and δ_{it}, λ_{it} and Ψ_{it}. Further, by using this method, one also obtains some preliminary results about how a student's family income, financial aid, and in-school wages affect his in-school employment decision. This information will prove useful in testing our theoretical model.

Notice that the above estimating model considers a student's work-time decision to be endogenous in nature, i.e., a function of factors such as family income, financial aid, etc.. Another method of obtaining unbiased estimates of WH_{it} on LnW_{ij} is to assume that WH_{it} is exogenous. The fixed effect of λ_{it} can then be differenced out, and the effect of WH_{it-k} on LnW_{ij} can thus be estimated.

Although there are two possible methods with which to estimate the effect, we consider the second method inappropriate for this study. The theoretical model presented earlier argued that a student's work time was endogenous; naturally, it would be inappropriate to change this assumption in the empirical section of the study.

2.2 The Data

In order to examine the effect of a student's in-school employment on his post-college success, we use pooled corss-section time-series micro data from the National Longitudinal Survey of Young Men 14-24, 1966-1975 (NLS). The NLS is a national longitudinal probability sample of 5225 young men who were initially interviewed in 1966 and who were between the ages of 14 and 24 at that time. Subsequently, person-to-person interviews were conducted through 1971, and telephone interviews, in 1973 and 1975.

The cross-section micro data from the NLS provides annual information on each student's employment status, hours of work, financial aid, and a host of other personal and family characteristics. The data also contains information on the post-college earnings of each student for several years. The sample employed in this part of the study is limited to those males who graduated with a bachelor's degree in 1969, 1971, and 1973. Students who attended graduate school or joined the military service after their graduation are excluded from the sample since no earnings data is available for them.[5]

There are two major reasons why the sample is limited as outlined above. First, we need complete information about students' in-school work experience throughout their college years. Students who graduated in 1969 typically finished their first year of college in 1966, which corresponded to the first year of the survey. However, there were only 52 students who graduated with a bachelor's degree in 1969 in the survey. In order to increase the sample size, we add those students who graduated with bachelor's degrees in 1971 and

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5. Potentially, a sample selectivity bias problem exists because I have excluded those students who attended graduate school or joined the military service. To keep the econometrics managable. I will, however, ignore this problem.

1973. Students who graduated in 1970 and 1975 are excluded from our sample since there was no survey made in 1972 and 1977, which would have contained third-year out-of-school earnings for these students. This pooling across years increases the sample size to 248 observations.

In studying the determinants of fifth-year post-college earnings, it is not possible to include those who graduated in 1973 in the sample; no survey was conducted in 1977 which again would have contained the required earnings data. Therefore, only included are those students who graduated in 1969 and 1971 because their fifth-year post-college earnings correspond to their earnings in 1973 and 1975, respectively. This restriction reduces the sample to 102 observations for this aspect of the analysis.

2.3 The Empirical Results

The empirical estimation strategy for the students' post-college earning model is as follows: first, we estimate the students' in-school employment equation (Equation 17). Second, we use WU tests to determine if the disturbances between the wage and employment equations are independent. Third, if the disturbances are independent, we can estimate directly the wage equations. If they are not, then the two-stage least squares method (2SLS) is appropriate.

We begin our empirical work by estimating employment equations to determine which factors significantly affect students' in-school work decisions. Table 1 lists variables used in the empirical models. Table 2 presents employment equations for students in their third and fourth years in college. In this table we find that increases in the student financial aid (Fin-Aid) variable reduce students' in-school employment. T-statistics for Fin-Aid are marginally significant in model 4, but they are clearly significant in models 1 and 2. An increase in the local area unemployment rate (local-U) also reduces studnets' work time in model 4, and students who live alone (L-Alone) tend to work more (models 1-2). In this model, we also find evidence that marriage and presence of children may increase students' work load.

The negative effect of financial aid on students' employment confirms the results of the theoretical model. But before we fully explore the policy implications of this result, we must ascertain what the impact of student financial aid is on students' post-college earnings, and how students' in-school work experience affects their post-college earnings.

As indicated previously, it is necessary to test the independence of the disturbances before the wage equations can be evaluated. In Table 3, WU tests are performed by including both the predicted weeks (or hours) worked variables and the original weeks (or hours) worked variables for the first, the third, and the fifth-year post-college earnings, respectively. Different specifications of models 1 to 4 suggest that the error terms between the wage and employment equations are not correlated for the first year out of college; the predicted weeks (or hours) worked variables are never significant, while the actual weeks (or hours) worked variables are generally significant. Based on the results of these tests, only the actual values of weeks (or hours) worked variables will be included in the first-year out-of-school wage equations. In models 5 to 8, predicted weeks (or hours) worked variables are significant, while the actual weeks (or hours) worked variables are not. Therefore, the error terms between the wage and the employment equations are correlated, and the 2SLS method should be used in the third-year wage equations. Similarly, WU tests in models 9 to 12 show that the error terms are correlated in the model, and the 2SLS method should again be used in the fifth-year wage equations.

Based on the results of the tests, the wage equations are estimated and the results are presented in Table 4.[6] In this table we find that students' in-school work experience significantly affects their first-year post-college earnings, as total weeks worked in the fourth year in college (WW4) is significant in models 1 and 2, and total hours worked in the fourth year in college (WH4) is significant in models 4 and 5.

There are several other results in the table that warrent mention. First, having first-year on-the-job training, Training1, appears to significantly lower earnings, at that time; a result consistent with human capital theory. Second, financial aid, marriage, SMSA, IQ, and race do not appear to have any significant, direct impacts on first-year out-of-school earnings. A third result is related to an argument raised in section 1, that the slope of the t_n-W_p function is theoretically indeterminant. To test that notion, some experimentation is conducted by including both weeks (or hours) worked and its square in the model. The results in model 3 suggest that the function may be concave from the origin since the sign of variable WW441 is positive while the sign of variable WW441S is negative (but neither are significant). In model 6, the concavity of the t_n-W_p function is confirmed since the variables WH441 and WH441S have the expected positive and negative signs and they are both significant.

The results in Table 4 clearly show that students' in-school work experience favorably affects their post-college earnings. However, model 6 suggests that if students devote increasing blocks of time to work, either voluntarily or involuntarily depending on their financial burden, ultimately their subsequent

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6. The state dependent variable was not included in the final wage equations since it was not clear from the survey whether the individual acquired his work experience at the beginning, at the end of the period, or even on and off during the period. Therefore, it proved impossible to pursue the concept of state dependence.

earnings might be affected adversely.

More specifically, one can determine, from models 3 and 6, where the effect of in-school employment on post-college earnings reaches its maximum. Solving for the value of WH at which post-college earnings is maximized, and assuming that the typical student works 37.92 weeks per year,[7] model 6 shows that if students work over 27.2 hours per week, then their in-school employment will have a negative effect on post-college earnings. This figure is consistent with Astin's findings that students who worked over 25 hours per week showed reduced study persistence.

In models 7 to 10 the results of the 2SLS estimation are presented for the third-year post-college earnings. Here we find that students' in-school work experience not only affects their first-year out-of-school earnings, but also affects their third-year out-of-school earnings; the predicted weeks (or hours) variables are significant in all models. Furthermore, models 9 and 10 show that hours of on-the-job training in the first year out of school have a positive effect on their third-year post-college earnings, variable Training1 is significant in these two models. The positive impact of Training1 on LnW_3, together with the negative impact of Training1 on LnW_1, is perfectly consistent with human capital theory.

In models 11 to 14 the estimates from the 2SLS method are presented for the fifth-year out-of-college earnings. The results suggest that students' in-school work experience has a significant impact on their post-college earnings for at least five years. Due to data limitations, however, the impact beyond the fifth year out of college cannot be evaluated.

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7. This is the value of weeks worked from model 3, in which post-college earnings would be maximized.

Table 5 presents Tobit estimates of the wage equation. The results are very similar to those of Table 4: weeks (or hours) worked variables are significant for at least five years out of college. Furthermore, the magnitude of the wage effect increases from the first year's 4.3 percent to the third year's 27 percent, but then declines to the fifth year's 2.5 percent for an additional week worked in the fourth year in college. The concavity of the earnings profile for an additional hour worked in the fourth year in college is also presented.

Having examined the impact of in-school work on post-college earnings, it is also important to evaluate its employment effect since both effects may be presented. One can examine the impact of students' in-school work on post-college employment by regressing students' in-school work on post-college weeks (or hours) worked. These results are presented in Table 6. Contrary to many studies of high school students that concluded that the effects of in-school work on subsequent out-of-school employment were significant,[8] this table shows no significant impact of in-school work on college students' post-college employment.

One possible explanation for this discrepancy is that the general skills high school students learn during their in-school work experience (reliability, etc.) may be important, or closely related, to their postgraduation jobs. However, for college students the nature of in-school part-time employment may be unrelated to the skills needed for post-college employment.

Thus far we have examined the impact of college students' in-school work on their post-college employment and earnings. Students' in-school work was shown to exert significant influence on students' post-college earnings for

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8. For instance, Stevenson (1978), Ellwood (1982), and Meyer and Wise (1982).

at least five years. No significant impact was found on students' post-college employment. As fare as student financial aid is concerned, no <u>direct</u> impact on post-college earnings was found. This does not imply, however, that financial aid has no indirect effect. Recall from our results so far that the t_n-W_p function may be concave, that is, an excess amount of work time for students may adversely affect their post-college earnings. Furthermore, the estimates of the employment equations suggest that financial aid alleviates students' work load. It is possible that by doing so it may enhance their study persistence. To empirically test this hypothesis and to explore factors that affect students' drop-out decisions, we turn to students' study persistence in the next section.

3. On Study Persistence

In section 1 of the theoretical model, we assumed that changes in student's financial aid would affect student's post-college earnings through changes in quality of school and nonwork time. The implicit assumption about this model is that no corner solutions occur. If, however, the possibility of corner solutions is permitted, then cuts in student financial aid may not only adversely affect post-college earnings, but may also increase the college student dropout rate.

A major research project on students' study persistence was done by Astin [1975]. In his study, Astin pointed out that students' on-campus employment might actually increase students' study persistence, while students' off-campus work in unrelated fields or disciplines might increase the likelihood of leaving college prematurely. In his empirical work, Astin also found that those students who had received scholarships or grants increased their study persistence as did those students who has received support from parents for college expenses.

Though Astin's study of students' study persistence is an interesting one, it suffers from two methodological deficiencies. First, Astin estimated models with dichotomous dependent variables, and hence the predicted probability of dropouts from his model might not be bounded by the zero-one range. Second, and more importantly, Astin failed to account for the sample selection bias problem in his model. Since each student contributes to the decision about whether he will stay in college, this decision must be explicitly modelled. To evaluate the impact of students' part-time employment and financial aid on their decisions to complete their college program, the well-known two-stage procedures described by Heckman [1979] can be used.

Suppose, for example, that a college student considering dropping out of college faces two different wage rates. The first is the wage rate he will actually receive after dropping out of school, say, W_{di}. The second is the discounted value of the wage rate that he expects to receive if he completes his college, W_{spi}. W_{spi} can be expressed as

$$(23) \qquad W_{spi} = \frac{W_{pi}}{(1+r)^t}$$

where W_{pi} is the student's postgraduate wage rate, r is the subjective rate of discount, and t is the expected period for completion of the degree program. It is clear that the longer is the expected period to complete college, the lower will be the value of W_{spi}.

The decision to drop out of school is based on a number of factors. However, other things being equal, the larger the difference is between W_{di} and W_{spi} the greater the likelihood is that the student will choose not to continue studying.

Let an individual's preference for dropping out of school (S_i^*) be determined by the difference in the utility (U) he receives from staying and from leaving school. Suppose utility in each state is a function of the relevant discounted wage rate:

$$(24) \qquad S_i^* = U(\text{discount wages of stay}) - U(\text{dropout wages})$$

If these utility functions are linear,

(25) $$S_i^* = a_1\left(\frac{W_{pi}}{(1+r)^t}\right) + \varepsilon_1 - a_1(W_{di}) - \varepsilon_2$$

(26) $$S_i^* = a_1\left(\frac{W_{pi}}{(1+r)^t}\right) - a_2(W_{di}) + \varepsilon^*$$

wjere $\varepsilon^* = \varepsilon_1 - \varepsilon_2$, and the ε^* represent all other factors that influence the utility in each state. Now, since the variables t and r cannot be observed directly, we assume that these two variables can be proxied by a set of variables, X', and hence

(27) $$S_i^* = a_1(W_{pi}) - a_2(W_{di}) + \beta^1 X^1 + \varepsilon^*.$$

Without loss of generality, we can scale S_i^* so that the critical value at which the student is indifferent to remaining or dropping out is $S_i^* = 0$. The student will then drop out of college and accept a job if and only if

(28) $$S_i^* = a_1(W_{pi}) - a_2(W_{di}) + \beta^1 X^1 + \varepsilon^* < 0.$$

Let S_i equal 1 if the student dropsout but zero otherwise then we observe

(29) $$\begin{cases} S_i = 1 & \text{if} \quad S_i^* < 0 \\ S_i = 0 & \text{otherwise.} \end{cases}$$

Now assume that

(30) $$LnW_{pi} = Z\gamma + \varepsilon_p \qquad \varepsilon_p \sim N(0, \delta_p^2)$$

(31) $$LnW_{di} = Z\beta + \varepsilon_d \qquad \varepsilon_d \sim N(0, \delta_d^2)$$

where the vector Z contains all the characteristics of the student that affect the values of W_{di} and W_{pi}. Since the condition for observing a student who drops out of college is that Equation (28) holds, it is clear that the distribution of the observed dropouts is truncated. In this model the wage equations, LnW_d and LnW_p cannot in general, be consistently estimated by ordinary least squares using the observed wage rates because $E(\varepsilon_d | S_i = 1) \neq 0$, and $E(\varepsilon_p | S_i = 0) \neq 0$. Heckman [1979] has described a way to estimate consistently this model, and his discussion is summarized below.

The strategy is first to estimate a reduced-form probit model of the decision to dropout, which includes all the X's and Z's as explanatory variables. The dependent variable used in this model is a dichotomous variable that takes the value of 1 if a student drops out of college and 0 otherwise.

From the resulting estimates one can generate Mill's ratios, and these can be added to the wage equations as an additional explanatory variable. As Heckman [1979] shows, Equations 30 and 31 can then be estimated consistently using the truncated samples and ordinary least squares methods. Finally, the structural probit model can be estimated by explicitly including the estimated wages from the previous step.

Basically, the sample used here includes all the freshmen who attended college during 1966 to 1970. By pooling all the freshmen in this period and by excluding those who temporarily dropped out of college, 1010 freshmen were obtained. Among this group 185 dropped out of college. Similarly, samples were collected for sophomores and juniors for the same perios. There were 807 sophomores in the sample, of whom 134 dropped out of college one year later; and there were 597 juniors, of whom 78 dropped out of college one year later.

Notice that to focus attention on the final estimation of the model, all the intermediate results from the freshman, sophomore, and junor models are reported in the Appendix, and only the final structural probit estimates for freshmen, sophomores, and juniors are presented in Table 7. This table suggests that IQ, school quality, race, SMSA, and health limitations all have significant but inconsistent impacts on students' dropout decisions; the signs of the coefficient often vary across years. Some consistent and significant effects can be found from other variables, however.

For example, the local rate of unemployment has an important effect on students' dropout decisions, with higher rates of unemployment producing lower probabilities of droppingout. Crucially, students' part-time work also has an adverse effect on study persistence. One possible explanation of this result is that students are very sensitive to the current labor market situation. When the labor market is in an upswing and the demand for labor is high, marginal students may work more and may drop out of college. In contrast, if the economy is in a downswing and demand for labor is low, then students may stay in college until the markets improves. Some support for this argument comes from the coefficients of the wage variable. They suggest that an increase in a student's discounted wages, if he graduates, will enhance his study persistence, while an increase in the student's dropout wage will increase the probability of his leaving college.

Although the financial aid variable does not have any significant direct effect on dropout decisions, it does have an indirect effect that operates through its influence on in-school hours of work. The significant positive effect of the latter on the dropout decisions supports the argument that financial aid enhances study persistence. One can show, for example, from model 2 in Table 2 and the junior model in Table 7, that when faced by a $500 cut in student financial aid a typical junior will increase his total annual hours of work by 161 hours, which is equivalent to an additional 7.7 hours of work per week.[9] This increase in the student's work-load will

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9. Dividing 161 hours by the average weeks worked (21 weeks) gives 7.7 hours per week.

increase his probability of dropping out of college by 16 percent. Similar calculations based on hours of work equations for freshmen and sophomores suggest increases in their probabilities of droppingout of 10 and 12 percent, respectively.

4. Conclusion

Previous studies of the effects of students' in-school work experience focused on high school students who did not go to college. Studies by Ellwood, Corcoran, and Meyer and Wise all concluded that high school students' in-school work experience significantly and positively affected their subsequent earnings and employment. However, given the difference between these students and college students, these previous studies did not necessarily imply that a similar conclusion was valid for college students' in-school work effect.

Since cuts in student financial aid have occurred during the Reagan administration and may occur again in the future, it is important for policymakers to know how students' financial aid packages affect their employment decisions and how the resulting changes in students' in-school work affect their study persistence and their post-college earnings. This study has presented both theoretical and empirical models which explicitly examine such problems.

One significant finding was that college students' in-school work experience appeared to have a positive effect on their post-college earnings for at least five years. The empirical evidence, however, did not find that in-school work experience positively influenced post-college employment levels. Hence, for college students, in-school work experience appeared to have only a subsequence wage effect, not an employment effect.

The empirical results also confirmed that the t_n-W_p function was concave from the origin. For example, in one specification the positive effect of in-school work experience on post-college earnings reached its peak at 27.2 hours per week — a figure which was consistent with earlier studies. Other factors, such as on-the-job training in the first year out of school, were found to have a significant negative and positive effect on the first- and the third-year out-of-school earnings, respectively — results which were perfectly consistent with human capital theory.

The theoretical model in section 1 also found that student financial aid might have a positive effect on students' post-college earnings, either through a reduction in students' work load or through an improvement in school quality. The empirical evidence presented in section 2 did confirm the argument that financial aid significantly reduced students' work effort and enhanced their study persistence. For exmple, one empirical specification suggested that a $500 cut in a junior's financial aid would increase his weekly hours of work by 7.7 hours, which would, in turn, increase his probability of dropping out of college by 16 percent. The policy implication of such a finding is that cuts in student financial aid may inevitably increase students' part-time employment, adversely affect students' chances of finishing their college education, and reduce their subsequent earnings.

Other factors, such as the local rate of unemployment, also appear to affect students' study persistence. An increase in the local rate of unemployment will enhance study persistence. For example, the simulation results based on the estimates in Table 7 show that a 1 percent increase in the local rate of unemployment will reduce a student's probability of dropping out by 13.8, 45.5 and 10.2 percent in the freshman, sophomore, and junior years, respectively.[10] This suggests that college students'

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10. The magnitude of the sophomore year result is sufficiently large to call its validity into question.

study persistence is also affected by the economic situation in general, a conclusion that is further supported by the evidence that an increased dropout wage induces greater numbers of dropouts, while an increase in their discounted post-college wages induces them to stay in school.

Finally, it is important to point out that although cuts in student financial aid may force students to work more, which may adversely affect students' study perisistence and their subsequent earnings, it will also make students gain some labor market experience, which according to the empirical results, favorably affects their post-college earnings. Hence the empirical evidence seems to suggest that cuts in student financial aid will "benefit" those students who finish their degree program, but will "hurt" those students who drop out of college due to an excess amount of in-school work. What then are the net effects of these two contrasting forces? Will cuts in student financial aid ultimately benefit or hurt students on average? To answer these questions, observe that a student's expected future earnings are given by

(32) $$E(\text{earnings}) = p * W_d + (1-p) * W_p$$

Here p is the probability of dropping out of college and W_d and W_p are the drop-out and post-college wages. Now, differentiating the above expected (future) earnings, E(earnings), with respect to student financial aid, S, and assuming changes in aid do not affect the drop-out wage, we obtain:

(33) $$\frac{\partial E}{\partial S} = \frac{\partial p}{\partial S} (W_d - W_p) + (1-p)\frac{\partial W_p}{\partial S}$$

In this equation $\frac{\partial p}{\partial S}$ is the marginal probability of dropping out of college when financial aid increases (calculated in the simulations above), (1-p) is the probability of staying in college, and $\frac{\partial W_p}{\partial S}$ is the marginal effect of student financial aid on post-college earnings, which include both its direct effect and its indirect effect which operating through its effect on in-school employment.

The magnitude of this derivative can be computed from the prior empirical estimates. Incorporating the above estimates and evaluating W_d, W_p, and p at their mean values, we obtain that $\frac{\partial E}{\partial S} < 0$. Indeed, the data suggest that the net effect of a \$500 cut in financial aid would be to increase the average student's expected earnings by roughly 1.4 percent.

The implication of this result is that the net effect of cuts in student financial aid may be positive, in the sense that the resources would become available for other uses and students' expected earnings would rise. Hence the result seems to suggest that a reduction in student financial aid may be socially justified. One shoud stress, however, the preliminary nature of the result and the use of data form an earlier period when college costs were substantially lower in real terms. Before serious policy statements are made, this study should be replicated using more recent data.

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Table 1

Means and Standard Deviations for Variables Used in Wage and Employment Equations

	Mean	S.D.		Mean	S.D.		Mean	S.D.
WW1	26.42	17.75	Dep	0.12	0.42	3rd Year Out of College		
WW2	28.60	18.55	SMSA	0.63	0.48	LnW3	300.62	128.14
WW3	23.31	19.92				PCWW3	45.21	13.04
WW4	22.38	15.00	4th Year in College			PCWH3	1925.58	701.94
WH1	857.33	628.09	Fin-Aid	213.28	595.03	Local-U	72.80	29.70
WH2	819.31	608.62	Local-U	51.03	19.70	Marital	0.83	0.37
WH3	938.20	606.62	Marital	0.41	0.42	Dep	0.30	0.53
WH4	891.57	600.92	Dep	0.18	0.49	SMSA	0.81	0.38
Duncan-F	42.98	25.22	SMSA	0.72	0.44	Training3	1599.94	2896.88
Duncan-M	45.06	22.83						
Race	0.86	0.34	1st Year Out of College			5th Year Out of College		
Health	0.04	0.20	LnW1	251.47	94.97	LnW5	359.52	286.36
IQ	112.41	13.30	PCWW1	13.46	8.23	PCWW5	48.46	9.93
Family-Y	10463.71	8703.16	PCWH1	441.86	399.07	PCWH5	2114.96	727.86
			Local-U	51.03	19.70	Local-U	71.57	26.62
3rd Year in College			Marital	0.41	0.42	Marital	0.87	0.33
Fin-Aid	375.10	519.14	Dep	0.18	0.49	Dep	0.56	0.77
Local-U	44.00	17.74	SMSA	0.72	0.44	SMSA	0.82	0.38
Marital	0.19	0.39	Training1	726.24	1595.79	Training5	695.16	898.75

WW4 — weeks worked in the fourth year in college

WW3 — weeks worked in the third year in college

WW441 — average weeks worked over four years in college

Table 1 (continued)

WW441S	WW441 squared
WW331	average weeks worked over first three years in college
WH4	hours worked in the fourth year in college
WH3	hours worked in the third year in college
WH441	average hours worked over four years in college
WH441S	WH441 squared
WH331	average hours worked for the first three years in college
WW2	weeks worked in the second year in college
WW1	weeks worked in the first year in college
WH2	hours worked in the second year in college
WH1	hours worked in the first year in college
Fin-Aid	total financial aid received
Local-U	local rate of unemployment
Duncan-F	current Duncan occupation index of father
Duncan-M	current Duncan occupation index of mother
Family-Y	family income in 1966
L-Alone	L-Alone=1 if student lives alone, 0 otherwise
Race	Race=1 if white, 0 otherwise
Marital	Marital=1 if married, 0 otherwise

Table 1 (continued)

Dep	number of dependents
SMSA	SMSA=1 if reside in SMSA, 0 otherwise
Health	Health=1 if individual has health limintations, 0 otherwise
IQ	IQ score
Exp	age
Exp^2	age squared divided by 100
Training1	total hours of on-the-job training in the first year out of college
Training3	total hours of on-the-job training in the third year out of college
Training5	total hours of on-the-job training in the fifth year out of college
LnW_1	logarithm of the respondent's real hourly wage rate in the first year out of school
LnW_3	logarithm of the respondent's real hourly wage rate in the third year out of school
LnW_5	logarithm of the respondent's real hourly wage rate in the fifth year out of school
PCWW1	weeks worked in the first year out of college
PCWW3	weeks worked in the third year out of college
PCWW5	weeks worked in the fifth year out of college
PCWH1	hours worked in the first year out of college
PCWH3	hours worked in the third year out of college
PCWH5	hours worked in the fifth year out of college
M-Educ	mother education

Table 1 (continued)

Pd****	predicted value of variable****.

Note: Earning variables, such as LnW_1, LnW_3, and LnW_5, are deflated by the consumer price index in the corresponding year to convert all earning figures to real terms. All other nominal variables, such as tuition, financial aid, and family income, are similarly treated. Some variables, such as marital status, number of dependents, SMSA, age and age squared, are updated as the period changes, while others, like IQ score, remain constant over time.

Table 2

The Employment Equations — Weeks (Hours)
Worked in the Third and Fourth Year in College
(absolute value of t-statistics)

	(1) WW3	(2) WH3	(3) WW4	(4) WH4
Constant	-12.094	1113.12	-59.39	-3788.47
	(.14)	(.41)	(.56)	(.88)
Fin-Aid	-.009	-.322	-.004	-.242
	(2.26)	(2.29)	(1.31)	(1.71)
Local-U	.39	-3.221	-.066	-4.089
	(.56)	(1.41)	(1.22)	(1.82)
Duncan-F	-.050	-1.515	-.063	-1.573
	(1.32)	(1.21)	(1.42)	(.86)
Duncan-M	-.087	-.006	.037	.276
	(1.59)	(.003)	(.60)	(.10)
Family-Y	.27D-3	.005	.24D-3	.008
	(1.45)	(.91)	(2.09)	(1.69)
L-Alone	19.835	821.90	-.438	-92.460
	(3.41)	(4.38)	(.15)	(.79)
Race	4.434	32.177	-.358	-20.063
	(1.58)	(.35)	(.11)	(.15)
Marital	5.530	-236.483	4.752	201.207
	(.99)	(1.32)	(2.24)	(2.30)
Dep	9.487	257.516	.170	-38.196
	(2.09)	(1.76)	(.07)	(.42)
SMSA	3.325	90.001	1.103	72.039
	(1.29)	(1.08)	(.47)	(.75)
IQ	.005	.995	-.083	-4.526
	(.07)	(.34)	(1.01)	(1.32)
Exp	2.510	-71.365	8.195	460.779
	(.35)	(.30)	(.96)	(1.31)
Exp^2	-.047	1.972	-1.48	-8.803
	(.31)	(.40)	(.85)	(1.22)
DF	230	231	227	227
R^2	.567	.428	.161	.185

Note: All equations include dummy variables of Duncan-F, Local-U, Duncan-M, Fin-Aid to account for nonreporting.

Table 3

WU Tests on the Wage Equations for The First, The Third, and The Fifth Year OUt of College[a]

(absolute value of t-statistics)

	LnW_1				LnW_3				LnW_5			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WW4	0.36 (4.13)		0.037 (4.03)		0.007 (.65)		0.38D-3 (0.03)		0.29D-3 (.09)		0.003 (0.74)	
WW3			-.008 (.78)				0.016 (1.29)				-.002 (.52)	
WH4		0.93D-3 (4.32)		0.89D-3 (3.95)		0.22D-3 (.91)		0.48D-4 (.71)		-.88D-4 (.88)		0.69D-5 (.07)
WH3				0.44D-3 (.46)				0.30D-3 (.79)				-.12D-4 (.11)
PdWW4[b]	0.015 (.33)		0.025 (.53)		0.150 (2.75)		0.191 (3.43)		0.033 (2.13)		0.035 (1.94)	
PdWW3			0.021 (1.52)				0.016 (0.98)				0.008 (.61)	
PdWH4		0.63D-3 (0.62)		0.12D-2 (1.03)		0.004 (4.67)		0.49D-2 (3.57)		.48D-3 (1.62)		0.43D-3 (1.82)
PdWH3				-.37D-4 (.07)				0.82D-3 (1.43)				0.13D-4 (.07)
DF	228	228	226	227	228	228	226	226	90	90	72	72
R^2	.208	.210	.217	.210	.120	.226	.156	.160	.123	0.12	.146	.135

a: All equations include Race, Marital, Dep, SMSA, Health, IQ, Exp, Exp^2, Fin-Aid, Duncan-F, Duncan-M, Family-Y, L-Alone, Training1, dummies for Training1, Duncan-F, and Duncan-M.

b: Variable Pd**** represents the nredicted value of variable ****.

Table 4

Wage Equations For The First, The Third, and The Fifth Year Out of College

(absolute value of t-statistics)

	LnW_1^a						LnW_3^b				LnW_5^b			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	1.999 (.14)	2.084 (.15)	-.575 (.04)	3.405 (.24)	3.330 (.24)	2.530 (.18)	25.328 (1.34)	22.905 (91.22)	34.23 (1.80)	32.172 (1.69)	13.510 (.93)	11.205 (.85)	14.582 (1.09)	15.399 (1.16)
Race	.651 (1.52)	.670 (1.56)	.653 (1.27)	.653 (1.53)	.653 (.39)	.498 (1.17)	.179 (.36)	.155 (.31)	.222 (.46)	.232 (.48)	-.132 (.57)	-.101 (.44)	-.134 (.60)	-.133 (.60)
Marital	.166 (.59)	.161 (.57)	.274 (.96)	.133 (.48)	.136 (.49)	.267 (.97)	1.091 (2.38)	-1.191 (2.67)	-1.096 (2.50)	-1.084 (2.47)	.295 (1.49)	.294 (1.49)	.268 (1.34)	.262 (1.32)
Dep	-.019 (.06)	-.004 (.01)	.065 (.21)	-.006 (.02)	-.014 (.05)	-.063 (.21)	-.035 (2.13)	-.036 (2.16)	-.030 (1.87)	-.031 (1.88)	-.131 (1.31)	-.119 (1.16)	-.118 (1.13)	-.103 (1.00)
SMSA	-.430 (1.49)	-.429 (1.48)	-.429 (1.44)	-.423 (1.47)	-.432 (1.50)	-.428 (1.50)	-1.019 (2.72)	-1.028 (2.74)	-.958 (2.60)	-.960 (2.61)	-.049 (.29)	-.047 (.27)	-.037 (.21)	.043 (.25)
Health	1.047 (1.72)	1.010 (1.66)	1.103 (1.76)	1.061 (1.75)	1.053 (1.74)	1.032 (1.71)	-.806 (1.21)	-.863 (1.29)	-.705 (1.07)	-.758 (1.15)	.072 (.21)	-.074 (.22)	-.048 (.14)	-.075 (.22)
IQ	-.006 (.59)	-.006 (.59)	-.006 (.54)	-.005 (.47)	-.005 (.47)	.230-3 (.02)	-.004 (.37)	-.005 (.38)	.003 (.24)	.003 (.24)	-.001 (.29)	-.560-3 (.08)	-.002 (.32)	-.002 (.32)
Exp	.320 (.28)	.319 (.28)	.547 (.46)	.174 (.15)	.184 (.16)	.159 (.14)	-1.660 (1.13)	-1.428 (1.02)	-2.464 (1.66)	-2.282 (1.54)	-.621 (.59)	-.465 (.49)	-.650 (.67)	-.715 (.75)
Exp^2	-.007 (.32)	-.007 (.32)	-.012 (.48)	-.004 (.19)	-.005 (.20)	-.003 (.14)	.027 (.99)	.023 (.86)	.043 (1.54)	.038 (1.39)	1.110 (.60)	.862 (.51)	1.135 (.64)	1.276 (.73)
Fin-Aid	-.140-3 (.84)	-.140-3 (.84)	-.220-3 (1.25)	-.110-3 (.62)	-.100-3 (.62)	-.180-3 (1.07)	.930-4 (.48)	.100-3 (.52)	.230-3 (1.19)	.220-3 (1.13)	.460-5 (.05)	-.350-5 (.04)	.110-4 (.13)	.140-5 (.01)
Duncan-F	-.014 (2.41)	-.014 (2.43)	-.015 (2.48)	-.014 (2.52)	-.014 (2.52)	-.013 (2.36)	.400-3 (.05)	.001 (.20)	-.002 (.37)	-.002 (.31)	.002 (.54)	.001 (.35)	.001 (.37)	.001 (.33)
Duncan-M	.006 (.75)	.006 (.74)	.006 (.73)	.007 (.89)	.007 (.88)	.007 (.84)	-.015 (1.67)	-.018 (1.92)	-.010 (1.15)	-.012 (.27)	.002 (.40)	.002 (.41)	.470-3 (.10)	.001 (.03)
Training1	-.410-3 (2.42)	-.420-3 (2.47)	-.460-3 (2.62)	-.360-3 (2.12)	-.370-3 (2.19)	-.470-3 (2.79)	.260-3 (1.35)	.240-3 (1.29)	.490-3 (2.45)	.490-3 (2.46)	.270-3 (.82)	.250-3 (.79)	.300-3 (.87)	.270-3 (.28)
Training3							-.370-4 (.43)	-.340-4 (.40)	-.220-4 (.26)	-.210-4 (.24)	-.510-5 (.09)	-.560-5 (.10)	-.170-4 (.30)	-.150-4 (.28)
Training5											-.250-3 (.86)	-.230-3 (.79)	-.220-3 (.76)	-.230-3 (.79)
WW4	.036 (4.01)	0.037 (4.09)					.198 (5.05)	0.194 (4.99)			.031 (2.15)	.030 (2.11)		
WW3	.002 (.33)						0.23 (2.06)				.0027 (.21)			
WW441			0.053 (1.28)											
WW331		-.002 (.24)						0.048 (2.05)				-.003 (.30)		
WH4				.930-3 (4.30)	0.940-3 (4.30)				0.005 (5.22)	0.005 (5.55)			0.380-3 (1.74)	0.380-3 (1.76)
WH3				.130-3 (.54)					0.810-3 (1.91)				0.120-3 (.37)	
WH441						0.390-2 (4.68)								
WH331					0.100-3 (.39)					0.001 (2.02)				0.320-4 (.08)
WW441S			-.700-3 (.84)											
WH441S						-.180-5 (3.90)								
Df	229	229	229	229	229	229	227	227	227	227	54	54	54	54
R^2	.199	.199	.153	.210	.210	.218	.228	.228	.245	.247	.171	.172	.152	.150

Note: Dummy valables of Training1, Duncan-F, Duncan-M, and Fin-Aid are also included in all equations to account for nonreporting

a the actual weeks (or hours) worked variables are used in the models.

b the predicted weeks (or hours) worked variables are used in the models.

Table 5. Tobit Analysis on the Wage Equations[a]

(absolute value of t-statistics)

	LnW_1^b				LnW_3^c				LnW_5^c			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WW4	0.043 (4.11)	0.044 (4.20)			0.273 (4.82)	0.271 (4.80)			.025 (2.52)	.026 (2.55)		
WW3	0.002 (.29)				0.021 (1.57)				-.005 (.1)			
WW331		-.003 (.28)				0.049 (1.71)				-.002 (.44)		
WH4			0.001 (4.40)	0.001 (4.4)			0.006 (5.20)	0.006 (5.23)			.44D-3 (2.19)	.45D-3 (2.02)
WH3			0.0001 (.53)				0.8D-3 (1.56)				.66D-5 (.05)	
WH331				.0001 (.40)				0.001 (1.68)				-.69D-4 (.43)
n	248	248	248	248	248	248	248	248	109	109	109	109
LnL	-507.19	-507.19	-505.59	-505.65	-521.01	-520.79	-518.756	-518.56	-65.76	-65.67	-66.46	-66.37

a: all the exogenous variables presented in Table 4 are also included in the Tobit estimation.

b: the actual weeks (or hours) worked variables are used in the models.

c: the predicted weeks (or hours) worked variables are used in the models.

Table 6

Employment Effect Equations

(absolute value of t-statistics)

Dependent Variable[a]

	(1) PCWW1	(2) PCWH1	(3) PCWW3	(4) PCWH3	(5) PCWW5	(6) PCWH5
WW4			.060 (.78)		-.002 (.06)	
WW3	-.005 (.19)		.017 (.27)		-.060 (1.34)	
WH4				.045 (.46)		.238 (1.59)
WH3		-.083 (1.71)		-.068 (.61)		.084 (.47)
DF	230	230	227	227	45	45
R^2	.088	.119	.180	.209	.391	.438

Note: Variables such as Race, Marital, Dep, SMSA, Health, IQ, Exp, Exp^2, Fin-Aid, Duncan-F, Duncan-M, Training, and Dummy Variables are included in the regression.

a: Variable PC**** represents post-college****.

Table 7

Probit Estimation for Students' Drop-out Decisions

(absolute value of t-statistics)

Dependent Variables

	Freshman DROP1	Sohpomore DROP2	Junior DROP3
Constant	5011.067 (8.12)	4583.189 (10.14)	3493.203 (6.48)
IQ	.228 (6.03)	-.238 (10.09)	-.844 (6.11)
School-Q	-.037 (4.31)	.016 (3.40)	.010 (2.11)
Race	-4.168 (5.62)	3.167 (6.20)	10.660 (5.78)
Marital	.891 (3.54)	-.029 (.09)	.088 (.36)
Dep	-.610 (3.11)	-.108 (.43)	.252 (1.16)
SMSA	-8.632 (7.02)	-1.828 (3.20)	5.851 (6.28)
Health	-6.533 (8.45)	-16.798 (9.50)	33.718 (6.17)
Exp	-63.897 (8.31)	-32.428 (8.82)	182.245 (6.14)
Exp^2	1.408 (8.40)	.793 (8.95)	-4.126 (6.15)
Fin-Aid	-.003 (.79)	-.20 D-3 (.05)	-.025 (.14)
Tuition	-.14 D-3 (.05)	-.22 D-3 (.61)	-.47 D-3 (1.81)
Local-U	-.138 (8.97)	-.455 (9.99)	-.102 (6.04)
WH	.68 D-3 (5.72)	.44 D-3 (2.24)	.10 D-2 (7.28)
Training	.028 (7.24)	.236 (5.80)	.68 D-2 (.06)
Family-Y	.89 D-5 (.60)	-.82 D-5 (.41)	-.20 D-4 (1.14)
$Ln\hat{W}_{stay}$	-826.15 (5.98)	-771.062 (10.12)	-1145.42 (6.34)
$Ln\hat{W}_{drop}$	36.431 (5.98)	8.224 (3.09)	166.36 (6.09)

DROP1=1	185	DROP2=1	134	DROP3=1	78
DROP1=0	825	DROP2=0	673	DROP3=0	597
n	1010	n	807	n	675
LnL	-1356.96	LnL	-1158.73	LnL	-506.26

Appendix 1

Probit Estimation to Generate Mill's Ratios for Freshmen Model

	Coefficient	t-statistics
Constant	-3.632	-.52
M-Educ	-.071	-.62
IQ	-.013	-2.54
School-Q	.004	1.72
Race	.026	.16
Marital	.560	2.46
Dep	-.085	-.67
SMSA	-.036	-.291
Health	.467	1.68
Exp	.290	.42
Exp^2	-.44 D-2	-.27
Fin-Aid	-.031	-1.61
Tuition	.47 D-3	3.25
Local-U	.65 D-2	2.14
WH	.57 D-3	7.37
Training	.014	3.55
Family	-.12 D-4	-1.36

Dropl=1	185
Dropl=0	825
n	1010
LnL	-630.60

Appendix 2

Estimated Wage Equations for Freshman Model

(absolute value of t-statistics)

	Dependent Variables	
	LnW_{stay}	LnW_{drop}
Constant	6.464 (22.64)	7.977 (2.76)
M-Educ	0.004 (0.81)	0.095 (1.11)
IQ	0.83 D-4 (0.46)	-0.004 (1.85)
School-Q	0.19 D-4 (0.26)	0.002 (1.42)
Race	-0.27 D-3 (0.05)	0.120 (1.64)
SMSA	-0.006 (1.59)	0.094 (1.54)
Health	-0.014 (1.75)	-0.38 (1.20)
Exp	-0.091 (3.32)	-0.354 (1.21)
Exp^2	0.002 (3.06)	0.009 (1.36)
Local-U	-0.27 D-3 (2.72)	-0.002 (1.45)
Training		-0.13 D-3 (0.98)
Mill-Ratio	-0.012 (1.36)	-0.172 (2.68)
DF	636	151
R^2	.078	.176

Appendix 3

Probit Estimation to Generate Mill's Ratios for Sophomores

	Coefficient	t-statistics
Constant	-12.445	-1.23
M-Educ	-.157	-.99
IQ	-.010	-1.89
School-Q	0.20 D-2	.84
Race	-.129	-.69
Marital	.152	.69
Dep	.115	.54
SMSA	.100	.70
Health	.581	.87
Exp	1.263	1.30
Exp^2	-.028	-.24
Fin-Aid	-.037	-1.19
Tuition	.25 D-3	1.54
Local-U	.51 D-2	1.58
WH	.51 D-3	5.54
Training	.261	1.30
Family-Y	-.95 D-5	-.97

Drop2=1	134
Drop2=0	673
n	807
LnL	-470.17

Appendix 4

Estimated Wage Equations for Sophomores

(absolute value of t-statistics)

	Dependent Variables	
	LnW_{stay}	LnW_{drop}
Constant	6.067 (17.9)	5.464 (0.82)
M-Educ	0.13 D-2 (0.24)	0.093 (1.00)
IQ	-0.30 D-3 (1.57)	-0.12 D-3 (0.04)
School-Q	0.16 D-4 (0.21)	0.09 D-3 (0.60)
Race	0.005 (0.91)	0.143 (1.53)
SMSA	-.11 D-3 (0.02)	0.199 (2.65)
Health	-0.025 (2.43)	-0.179 (1.18)
Exp	-0.048 (1.51)	-0.196 (0.30)
Exp^2	0.001 (1.60)	0.005 (0.37)
Local-U	-0.59 D-3 (5.49)	-0.13 D-3 (0.08)
Training		-0.30 D-4 (0.13)
Mill-Ratio	-0.006 (0.64)	-0.025 (0.35)
DF	539	105
R^2	0.077	0.099

Appendix 5

Probit Estimation to Generate Mill's Ratios for Junior Model

	Coefficient	t-statistics
Constant	-21.033	-1.64
M-Educ	-.15 D-2	-.01
IQ	.46 D-4	.02
School-Q	.55 D-2	1.94
Race	-.318	-1.09
Marital	.168	.75
Dep	.124	.60
SMSA	.199	1.04
Health	.696	1.79
Exp	1.720	1.46
Exp^2	-.040	-1.50
Fin-Aid	-.027	-1.24
Tuition	.48 D-3	2.13
Local-U	.57 D-2	1.58
WH	.90 D-3	7.41
Training	.060	.56
Family-Y	-.16 D-4	-1.04

Drop3=1	78
Drop3=0	597
n	675
LnL	-410.92

Appendix 6

Estimated Wage Equations for Juniors

(absolute value of t-statistics)

	Dependent Variables	
	LnW_{stay}	LnW_{drop}
Constant	5.245 (16.95)	14.96 (1.95)
M-Educ	-0.006 (1.09)	-0.041 (0.99)
IQ	0.11 D-3 (0.57)	0.58 D-2 (1.39)
School-Q	-.15 D-3 (1.81)	0.001 (0.59)
Race	-0.002 (0.24)	-0.074 (0.47)
SMSA	0.002 (0.50)	0.017 (0.16)
Health	-0.001 (0.15)	-0.200 (1.05)
Exp	0.033 (1.23)	0.855 (1.20)
Exp^2	0.77 D-3 (1.28)	0.019 (1.20)
Local-U	-0.37 D-3 (3.78)	-0.002 (0.69)
Training		0.37 D-3 (0.61)
Mill-Ratio	-0.004 (0.39)	-0.021 (0.12)
DF	462	56
R^2	.045	.172

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