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THE IMPACT OF THE MARKET AND THE FAMILY ON YOUTH ENROLLMENT AND LABOR SUPPLY

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ABSTRACT

This paper analyzes the school enrollment and labor supply decisions of teenagers and young adults as jointly determined outcomes. The empirical results are based on an application of discrete multivariate analysis to a sample taken from the Survey of Income and Education. Higher relative wage offers are found to reduce the probability of a youth enrolling in school and to increase labor supply. However, the estimated impacts are very sensitive to adjustments made for the possibility that wage rate offers by firms are higher for full-time than for part-time work. Job availability, as measured by the local youth unemployment rate, has its strongest effect on the probability of enrollment and full-time labor force participation for nonwhite males, accounting, in the extreme, for a difference in this probability of almost 50 percent. Since a wage measure is included as an independent variable, we can be sure that the job availability measure is not acting as a surrogate for an absent wage variable, but instead has an impact of its own. Specific findings on the influence of various family and market characteristics are compared to those from earlier studies.

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This paper analyzes the separate influences of the labor market and the family on the school enrollment and labor supply decisions of teenagers and young adults. For a sample drawn from the 1976 Survey of Income and Education, the analysis considers explicitly two market signals pertaining to the relative reward for participation by the youth in the labor market. These are: (i) the wage, and (ii) the youth unemployment rate in the relevant local labor market, which is used as a measure of job availability. Data reflecting each family's socio-economic circumstances are also used in the analysis. As a result, it is possible to examine directly the impact of the family on the youth's decisions and to separate this from the impact of the labor market characteristics. This permits us to discern, among other things the added worker and discouraged worker effects.

Decisions as to whether to participate in school and/or the labor force are qualitative in nature and are jointly determined. The empirical portion of the study uses discrete multivariate analysis, a relatively new statistical technique suitable for analyzing jointly-determined qualitative decisions, to estimate youth enrollment and labor supply functions. In a separate paper (Steinmeier, 1979), it is demonstrated formally that multinomial logit analysis applied to analyze an identically specified model would generate identical results. However, in the context of our problem, multinomial logit analysis would be more expensive to use and more difficult to apply than discrete multivariate analysis.

While other studies have been concerned with various aspects of the school enrollment-labor supply decision, there is no <u>single</u> set of estimates which: (a) incorporates information on the youth, the youth's family, and the market; (b) considers the roles of both job availability and the wage; and

(c) uses econometric tools that would be viewed today as being appropriate for analyzing these enrollment and labor supply decisions. As a result, the findings of these past studies--many of which were conducted before appropriate analytical tools were developed--are likely to be biased, either because they used inappropriate techniques (e.g., OLS to analyze qualitative outcomes) or because the enrollment or labor supply relations were not fully specified, subjecting parameter estimates to specification bias.[1] To provide an indication of how serious these biases may be, our findings are compared in detail with those from the most complete and important of the earlier studies, Bowen and Finegan's pathbreaking work (1969) and the ambitious effort by Cohen, Rea, and Lerman (1970). Comparisons with results from other studies are also presented. While there are differences between our study and earlier ones in the periods covered, variable definitions, and other factors, all of which lead us to expect some differences in results, a major purpose of this study is to highlight those areas where quantitative estimates differ very significantly from those reported elsewhere. Equally important, it is of interest to discover which findings from earlier studies persist.

For those who work, we also attempt to discover how family background and market conditions influence the propensity for part-time vs. full-time

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[1] To the extent that downwardly rigid wages prevent the youth labor market from clearing, one would expect both wages and job availability to influence labor supply. If one of these measures is not included in explaining labor supply, the coefficient estimated for the other measure may, for well known reasons, be biased. In addition, in the alternative circumstance in which the youth labor market does clear, if the wage is not included as an independent variable and standardized for statistically, one might find that a measure of job availability--such as the proportion of industries in a community that normally employ teenagers--is significantly related to the quantity of labor supplied. Unless the wage is held constant, findings with respect to demand related factors which normally influence the quantity of labor supplied by operating through the wage rate may erroneously suggest that job availability plays an independent role in influencing labor supply.

participation, and how this is related to the enrollment decision. Consider, for example, the potentially conflicting effects of job availability on school enrollment and the interrelation with part-time employment. On the one hand, if jobs are readily available to young people, youth from poor families may be able to enroll in school, supporting themselves through part-time work. With no jobs available, some may be unable to afford school expenditures and may drop out (Bowen and Finegan, 1969, p. 404). On the other hand, readily available employment opportunities for youth may simply raise the probability of dropping out of school and working full-time. Our findings will help to determine how young people react to this influence and to other influences of the market.

Much of the public concern about the operation of the youth labor market has focused on the very high unemployment rates for nonwhites and the impact of these high rates on minority youth. In view of this concern, and also in view of the likelihood that the labor supply and enrollment functions may be different for young men from those for young women, we fit separate functions for those in each race-sex category and highlight the differences among the groups. While much work remains to be done, it is our hope that this paper will take policy-makers a step closer to having the kind of estimates of enrollment and youth labor supply functions that can be used to isolate the effects of the market and the family on the youth's enrollment and labor supply decisions. Such estimates are required if policy-makers are to distinguish the impacts of current youth-oriented labor market programs from those of market forces, and if they are to be able to predict the impact of proposed policies.

We begin by sketching a theoretical framework which builds on the time in the household approach. A second section discusses the empirical specification and the estimation techniques used. The empirical results in Section III analyze the influence of the market and the family on the enrollment and labor supply of the over 18,000 young people in the sample and compare the results to those from other major studies of youth enrollment and labor supply. A concluding section discusses the relation of these results to current policy.

I. Theoretical Framework

The analytical framework builds directly on Gronau's (1977) recent model of the allocation of time. The youth is assumed to be the decision-maker, but the family influences the youth's decisions through a number of channels. Utility is determined according to the following function:

$$V = V(Z[(X + X_P[H_H]), H_L], Z_F[E_O, H_E], E[E_O, H_E], \mathrm{Fam}) \tag{1}$$

To preserve space, a number of structural relations discussed in more detail in Gustman and Steinmeier (1979) have been collapsed into V. The function Z represents current commodities produced by purchased goods (X), by goods (X_P) produced from time spent in the household (H_H), and by leisure time (H_L). Z_F is a function representing the current value of commodities to be produced in future periods. It is assumed that commodities will be produced in future periods so as to generate optimal investment, production in the household, and consumption patterns in all periods <u>after the one under observation</u>. The amount of future goods available is a function of total education accumulated up to the beginning of the period of observation (E_O) and time devoted in this period to educational activities (H_E) which together determine the amount of human capital inputs to the earnings function in future periods.[1] Education

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[1] Educational inputs purchased might also be included in E. But to do so requires us to consider the price of educational goods. There is no convenient measure of the price of educational goods available for use in the empirical analysis.

(E) is also assumed to influence independently the level of utility. Finally, Fam represents the influence of family characteristics. Family characteristics influence each of the commodity production functions listed, the youth's preferences and knowledge of the available choice set. They may also play a role because the youth cares about the family and may alter behavior in accordance with the family's circumstances.[1] For convenience of presentation, Fam has been included only once in Equation (1).

Equation (2) represents the time constraint facing the youth. It is assumed that T, total discretionary time available, is constant.

$$T = H_N + H_H + H_E + H_L. \tag{2}$$

The other budget constraint pertains to goods:

$$P \cdot X = W \cdot F(H_N, U) + I. \tag{3}$$

P is the price of all goods (X) purchased in the market; W is the wage rate;[2] H_N is the hours in the labor force; U is the unemployment rate; and I is other

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[1] One possibility suggested by Ehrenberg and Marcus (1979) is that there is a minimum contribution to the family required of young people from poor households. Such a requirement may modify either the utility function, the budget constraint, or both. If this effect is important, they note that, where jobs are scarce, a young person who might otherwise work part-time and attend school might be forced to drop out and look for work full-time. Goldfarb and Yeazer's analysis, which utilizes a Stone-Geary specification for the utility function, is consistent with this view. Our empirical analysis includes a test for the presence of the interaction effects between family income and the local area unemployment rate which are implied by two hypotheses, but the interaction is found not to be significant.

[2] Rosen (1976) has shown how to incorporate into the analysis a wage that varies with hours supplied. He includes a measure of the total earnings associated with different amounts of time spent at work rather than just using the wage rate to explain time supplied to market work. Such an adjustment would complicate but not change the thrust of the theoretical model. Accordingly, at this point we assume the wage is invariant with hours. To examine the importance of this assumption, the empirical analysis utilizes as an alternative to the observed wage an adjusted wage which is calculated at a particular amount of hours worked.

income. For a young person, much of I is expected to take the form of transfer income from and to other members of the family.[1]

Time that is actually spent in market work, generating income at the wage rate of W is measured by $F(H_N,U)$, which is less than H_N. The difference between time supplied to the labor market and time spent at work is accounted for by time spent unemployed, either in job search or idle time. Since some labor force time is spent in activities that do not generate income, the likelihood of spending some fraction of labor force time in unemployment reduces the expected returns from labor force time.[2] Accordingly, when optimal decisions are calculated, the attractiveness of labor force participation may be expected to vary inversely with the unemployment rate. While many approaches may be taken to modeling the role of unemployment as it affects job choice, the simple specification in Equations (1), (2), and (3) captures the spirit of the discouraged worker effect as visualized in the labor force participation literature.[3] However, in view of the simplifications involved, no assumption

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[1] A more elaborate analysis would allow transfers to vary with educational choice. This would reflect both a family's willingness to finance educational but not other types of expenditures, and the availability of governmental and other loans only to those who are enrolled in school. Another extension would incorporate the linkage between future earnings and desired current period consumption (see Gustman [1973] and Gustman and Stafford [1972]).

[2] The probability of a new entrant obtaining a job will depend on the unemployment rate and on turnover of those who are already employed. If, for any given unemployment rate, turnover is high enough so that unemployment is shared by all those who are in the market, the unemployment rate may provide a direct indication of the fraction of labor force time that a typical individual will spend unemployed (Gramlich [1976]). For an analysis which considers the interrelations between the minimum wage, job turnover, unemployment, and the likelihood of securing a job, see Mincer (1976).

[3] The model could be further modified to consider own unemployment as a state that involves (dis)utility that is different from the disutility of working. The differential productivity of search from unemployment rather than search from employment might also be considered.

is made about the specific functional form of F and therefore about how unemployment time varies with total time committed to the labor force.[1]

Maximization of (1) with respect to the uses of time (H_N, H_H, H_E, and H_L), the quantity of goods purchased (X), and Langrangian multipliers representing the marginal utility of time and money, subject to Equations (2) and (3), yields a system of reduced form equations for each of the various uses of time and goods purchased.[2] The equations we focus on are those for time spent on educational activities (H_E) and time supplied to the market (H_N). These are:

$$H_N = H_N(\text{Fam}, W, P, U, I, E_O) \tag{4}$$

$$H_E = H_E(\text{Fam}, W, P, U, I, E_O) \tag{5}$$

Consider now the role of stochastic elements in the model. Clearly, utility functions are not the same, even for youths with the same set of observable characteristics. Differences in tastes for work and education arise from factors we cannot measure, and the same is true for the kind and amount of parental advice. These factors serve to introduce stochastic elements into

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[1] In an analysis of the effect of unemployment on labor supply, Rea (1974) assumes that unemployment time is not a function of time spent in the labor force.

[2] This procedure assumes rational decision-making on the part of the youth. A number of objections may be raised to this assumption. One is that, despite the intuitively appealing nature of the marginal conditions for maximization, the calculations required are too difficult for it to be assumed that the "as if" hypothesis can legitimately be adopted. Another objection is that in some cases the youth's activities may conflict so obviously with his or her own self-interest that defending the rationality assumption involves the tautological argument that if the youth acted in a particular way, there is some goal that he or she had in mind which was being maximized. On the other hand, it is our judgment that by using the analytical framework suggested by the theory in combination with the (relatively flexible) statistical technique we employ, which does not require narrow assumptions as to functional form, there is a smaller probability that the results will be contaminated by serious specification error than if any available alternative approach is taken.

any parameterization of the utility function. Furthermore, there may be some unmeasured constraints that vary from family to family, such as difference in the conditions upon which income is transferred from the parents to the youth.

As a result of these unseen random factors, H_N and H_E are not completely determined by the observed explanatory variables in Equations (4) and (5) (although they may be completely determined by some larger set of observed and unobserved explanatory variables). Rather, H_N and H_E have a probability distribution for any particular set of values of the observed explanatory variables. The relation that we estimate is

$$\mathrm{Prob}(H_N, H_E) = F(\mathrm{Fam}, W, P, U), \qquad (6)$$

where the dependent variable is the joint probability that a youth works H_N hours and goes to school H_E hours. The estimation procedure (to be discussed below) does not require us to specify the functional form of F in Equation (6). For consistent parameter estimates, however, the usual assumption that the stochastic errors are uncorrelated with the explanatory variables is necessary.

In addition to the introduction of stochastic elements, the transition from Equations (4) and (5) to Equation (6) involves two other changes. First, since there is no information on the nature of intrafamily transfers which make up the bulk of the youth's income (I), it is assumed that I is a function of family income and background. Therefore, the variable I does not appear directly in Equation (6). The second difference is that E_0 does not appear in Equation (6). It is assumed that past family and market circumstances persist sufficiently over time so that it is possible to substitute iteratively for enrollment in each of the past years. The role of past enrollment outcomes is then approximated by writing them as functions of current measured family and local market characteristics. The reason we adopt this procedure is that at least some youths may make a single lifetime educational decision. If this is so, E_0 and the dependent enrollment variable will be simultaneously determined. Substituting iteratively for E_0 permits us to avoid the problems that arise if E_0 is endogenous to the decision-making process.[1]

II. Empirical Specification and the Estimation Procedure

The Survey of Income and Education (SIE) is a large cross-section survey built around questions from the Current Population Survey. The sample was taken from April through July of 1976. We work with observations for over 18,000 young people who live in one of the 98 largest SMSA's and who do not have a health problem. For this group, the survey identifies the name of the SMSA, which allows us to calculate relevant labor market measures and to incorporate them into the analysis, and hence to estimate the separate influences of the market and the family.

Activities of young people that are of interest to us can, for convenience, be divided into six mutually exclusive categories. The first major division indicates whether or not the youth was enrolled in school after February 1, 1976. Those enrolled in school fall into one of three categories: those who were not in the labor force in 1975, those who were in the labor force for 20 weeks or less (many summer-only workers will fall in this category), and those who were in the labor force for more than 20 weeks. For those not enrolled in school after February 1, 1976, the three categories are: in the labor force

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[1] Evidence that the distribution of unemployment rates among areas persists over time so that current area unemployment rates provide an indication of relative unemployment in a market in past periods is presented by Bowen and Finegan. For a further discussion, see Hall (1970) and also Holt (1978).

last year for less than 100 hours, in the labor force last year for 100 to 1200 hours, and in the labor force last year for more than 1200 hours.[1]

The independent variables are categorical. Limits for each category are chosen to correspond to commonly used classification terms (e.g., less than high school education, high school graduate, etc.) and/or to generate a relatively even number of observations in each category. Independent variables pertaining to the family are as follows:

The level of family income exclusive of the youth's own earnings:

Y:1	<$10,000
Y:2	$10,000-17,500
Y:3	$17,500-25,000
Y:4	>$25,000

The education of the head of the youth's family:

PE:1	less than a H.S. graduate
PE:2	H.S. graduate
PE:3	some college
PE:4	college graduate

The number of parents living at home:

P:1	one
P:2	two

[1] Note that since the sample was taken in the months from April through July, including time when students may be looking for or engaged in summer work, current status during the month of the survey may be a particularly misleading indicator of the activities pursued by the youth over the course of the year. Therefore, we have focused on time spent in the labor force last year (1975). It should be noted that we decided to base the part-time labor force measure for students on weeks worked last year rather than on hours worked because of the problem in interpreting the answer to the usual hours per week question for students who work both during the summer and part-time while in school.

The enrollment question does not refer to exactly the same time period as the time in the labor force question. Since there is no information on enrollment status during the past year, some people may be classified as having part-time labor force commitment when in fact their commitment was full-time. For example, those who went to work on a full-time basis after leaving school in June 1975, but who did not work while in school, will not have worked more than 26 weeks last year and most likely will not be enrolled after February 1, 1976. Therefore, they are likely to fall into the not in school, 100 to 1200 hours in the labor force category.

Whether the head of the family is employed:

Emp:1	no
Emp:2	yes

These measures of family background are self-explanatory.

Three age categories are employed.[1] They are:

A:1	17-18
A:2	19-20
A:3	21-22

We use two measures pertaining to conditions in the labor market, the wage of the youth relative to the average wage for high school graduates over 25 in the SMSA and the probability of finding a job as reflected in a youth specific unemployment rate. The four categories for the wage measure are:

W:1	<0.296
W:2	0.296-0.438
W:3	0.438-0.627
W:4	>0.627

The numerator of the youth wage variable is calculated as the ratio of the youth's earnings to the product of the usual hours worked per week and the number of weeks worked in 1975. These calculated wage rates for youth are then divided by a fixed weight measure of the average adult wage rate in the city where the young person lives.[2]

Youth unemployment in the area is measured by a fixed weight index using national weights calculated according to age, race, and sex, and is estimated as the ratio of time spent unemployed to time spent in the labor force in

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[1] Those who were 16 at the time of the survey are excluded because they were 15 during some part of 1975. Legal limitations on the kind of jobs they can hold and school attendance requirements restrict the freedom of fifteen-year-olds to choose between work and schooling options.

[2] The deflated wage variable measures the relative reward to working while still a youth. The adult wage rate reflects, at least in part, inter-area differences in the cost of living. Accordingly, we do not, as called for by Equation (6), also deflate by an index of cost of living (P).

1975. There are three categories for the unemployment variable:[1]

U:1	<16.4%
U:2	12.2-16.4%
U:3	>12.2%

Econometric estimates used in this study are based on the discrete multivariate algorithm developed by Goodman (1968, 1971) and others for dealing with a model consisting of categorical dependent and independent variables. Bishop, Feinberg, and Holland (1975) discussed the approach in detail. Using this technique we are able to estimate the effects of variation in the independent variables specified above on the probability that a youth falls in a given school enrollment-labor supply category. It may be shown that the discrete multivariate algorithm maximizes exactly the same likelihood function as does the standard multinomial logit algorithm, and hence the two sets of estimates must be equivalent.[2] We chose to use discrete multivariate analysis because it is flexible--i.e., it requires no rigid assumption about functional form--and is a relatively inexpensive technique to use for analyzing very large data sets in a situation where there are only a few explanatory variables.[3]

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[1] Similar results are obtained when an alternative measure of area unemployment--one based on the rate of unemployment at the time of the SIE survey--is used.

[2] The equivalence requires that the full set of interactions among the explanatory variables (but not involving the dependent variable) be included in the discrete multivariate model; see Steinmeier (1979). The algorithm actually used in the study assumes that family characteristics are only weakly correlated with area labor market characteristics so that some third-order and higher interactions between these two groups of <u>independent</u> variables are ignored. All second-order interactions are considered, however.

[3] In a report upon which this paper is based (Gustman and Steinmeier, 1979), for purposes of example, we solved the model specified in Equations (1) through (3), assuming simple Cobb-Douglas-type production and utility functions. It is clear from this exercise that the underlying relations are nonlinear. An estimating technique which uses categorical explanatory variables, as discrete multivariate analysis does, facilitates an analysis of nonlinear relations. Moreover, discrete multivariate analysis facilitates the study of interactions among independent variables, which we expect to occur.

In discrete multivariate analysis, the central statistic is G^2, which is -2 times the log-likelihood function:

$$G^2 = -2 \sum_{i=1}^{n} f_i \log(\frac{f_i}{p_i}),$$

where p_i is the probability predicted by the model for a combination of values from the actual data, and i runs over all possible combinations of variables. Estimating an additional effect (or interaction) will tend to reduce G^2, and the significance of the effect is inferred from the size of the reduction. Under the hypothesis of no true effect, an additional estimated effect will yield a ΔG^2 which has a χ^2 distribution with the degrees of freedom equal to the number of additional independent parameters introduced by the effect. If the ΔG^2 is above the appropriate critical point on the χ^2 distribution, the effect (or interaction) is deemed to have a significant impact on the dependent variable. Thus, the ΔG^2 statistic tests the joint significance of a group of dummy variables defining the categories of an explanatory variable. A value of the ΔG^2 statistic pertaining to the relation between the indicated independent variable and the set of enrollment-labor force outcomes is reported, where appropriate, in the last column of the tables in Section III.

There are two missing data problems which the econometric procedure must accommodate. The first pertains to the wage rate for those who did not work last year. For those youths, the distribution of potential wage rates is taken from an earnings function based on age, sex, race, and labor market (i.e., SMSA), and estimated from those who did work. A major concern in following this procedure is that those who did not work are different from those who did in a systematic fashion that will lead to the results being contaminated by selectivity bias. However, tests for selectivity bias indicate that it is not a significant problem.[1]

The second data problem arises because if a young person has either discontinued schooling and left home or has married and left home, characteristics pertaining to the youth's parents' household are not reported. This problem is not very serious for the younger members of the group we are concerned with, especially because the SIE reports family characteristics for young people who are not married but are in schools away from home. However, for the older cohorts, a larger fraction of observations in the sample have no data reported on parental family characteristics. Since a youth is unlikely to leave home and school without a means of support, those with missing information are more likely than average to be working, at least in the case of male youth.[2]

Given that information on family characteristics is missing, one of two courses can be taken. The analysis can be limited to those for whom a full set of data is available. The problem with following this course is that since the young people who leave their parents' home are likely to be those able to support themselves, while some who remain home cannot, the effect of independent variables on school-work choice is conditional on remaining at home. Hence,

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[1] An appendix describing the tests is available from the authors on request. For a discussion of selectivity bias, see Heckman (1974, 1976) and Cogan (1977).

[2] The percentage of the entire population with missing data is reported in the following table.

Percent of Youth by Age, Race, and Sex
with Family Data not Available

	White		Nonwhite	
Age	Male	Female	Male	Female
17-18	5	12	4	9
19-20	21	38	14	30
21-22	46	62	36	57

the findings would be difficult to interpret and not representative for a typical youth in the population. Alternatively, it is possible to estimate the distribution of family background variables for those for whom no data are reported. Estimates can be obtained by assuming that parental family income, education, and structure are the same for the younger cohorts, for whom family data are available for almost everyone, as they are for the older cohorts, for whom we have family data on only a subset.[1] The distribution of family characteristics for the subset of the older cohort with no data reported can then be estimated as the difference between (a) the characteristics for the entire older cohort, as projected from the younger cohort, and (b) the family characteristics for the subset of the older cohort for whom we do have data. In practice, we use discrete multivariate analysis to estimate separate distributions for the younger cohorts and for those in the older cohorts who remain home. After adjusting for size differences among the cohorts, the probability distribution for those with missing data is calculated as the difference. This method of projection, which is roughly analogous to using averages for missing observations in OLS, is not without its problems,[2] but projecting the missing data and including all observations appears to be a better choice than simply eliminating from the sample all those who left home.

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[1] This assumption cannot, in practice, be fully justified. For example, the number of families with two parents may be lower for 20-year-olds than for 17-year-olds because the parents of 20-year-olds are older and more of them are likely to have died. Nevertheless, in our calculations we assume as an approximation that the distribution of family characteristics is the same for younger and older cohorts.

[2] As a result of this procedure, the effects of family background characteristics may be biased downward, especially for older youth who have left home in greater numbers. Experimentation indicates that the estimated effect of market factors on labor supply and enrollment is not very sensitive to the assumptions made about the relation between family income, labor supply, and enrollment within the group that has left home.

III. Empirical Results

The empirical results are organized in the following way. First, Table 1 summarizes the effects of personal characteristics--age, race, and sex--on the probability of falling into one of the schooling-labor force groups specified. The probabilities presented in Table 1 are calculated for what we will call a reference youth--that is, a youth from a family with chosen characteristics facing reference level labor market conditions.[1] Specifically, the reference youth is assumed to be from a family with an income that is in the second category ($10,000-$17,500), to have a family head with an education level that is in the second category (high school graduate), to be from a two-parent family, and to be from a family with a head who is employed. This reference youth faces a wage offer that falls in the second category (30 to 44 percent of the average adult wage) and lives in an SMSA with a youth unemployment rate that falls in the middle category (13.6-17.6 percent). It is important to remember that these data are not simple cross-tabs, but compare probabilities for different age, race, and sex groups holding family background and labor market characteristics constant. Tables 2A through 2F, which are presented later in this section, examine the effects of variation of each of the independent variables on the probability of a youth falling into one of the work-schooling categories.

The first six columns of each table refer to the joint probabilities of a youth falling into one of the six school enrollment-labor force categories defined above. The remaining six columns of probabilities are derived from the joint probabilities presented in the first six columns. Columns 7 and 8 refer to the marginal (i.e., unconditional) probabilities of school enrollment

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[1] The actual parameters estimated, which underlie the probabilities presented in each of the tables in the text, are available from the authors on request.

and labor force participation, respectively. Columns 9 through 12 deal with the conditional probabilities of being in the labor force or in school. Column 10, for example, considers the probability of labor force participation, given that the individual is not enrolled in school.

The conditional probabilities are computed primarily for purposes of comparison with earlier studies. Many who dealt with this issue previously did not have the techniques of multinomial logit or discrete multivariate analysis available to them, and instead took the approach of analyzing conditional distributions.[1] As the discussion of Bowen and Finegan indicates, however, the parameters of conditional distributions are by themselves tricky to interpret.[2] To illustrate, consider the effect of higher family income on labor force participation conditional on being in school. This effect is composed of two parts: (i) For each person who was in school at the lower income level, the higher income level changes the probability that he or she will be in the labor force. (ii) The higher family income may cause some people who were not enrolled originally to become enrolled. They may have had a much different propensity to be in the labor force, and the fact that they are now in the

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[1] Three recent papers apply the multinomial logit technique to data from the National Longitudinal Survey. One analyzes the joint determination of school enrollment and labor force participation (Antos and Mellow, 1978); another, changes in enrollment and employment status (Stephenson, 1978). Neither study includes a direct measure of the wage in examining market impact. The third study (Ehrenberg and Marcus, 1979) investigates the effect of minimum wage laws on employment and enrollment status. Notice that employment status is an outcome of supply and demand interactions. Our concern is with the supply side relationship where the quantity measure pertaining to the labor market is time supplied to the market.

[2] Bowen and Finegan essentially combine a labor supply function conditional on enrollment status with a marginal equation describing the determinants of enrollment to derive a joint probability of labor force participation and enrollment status. Lerman (1972) takes an analogous approach to explaining enrollment behavior. However, while he discusses the determinants of enrollment status for youth conditional on labor market status, he combines that with an analysis of labor market status conditional on enrollment status.

enrolled group will affect the conditional probability under consideration. These two effects, which Bowen and Finegan call a "pure" effect and a "shift" effect, are muddled in a conditional distribution, with the result that the parameters of an estimated conditional distribution cannot be interpreted as the marginal effect of an explanatory variable on the probability of a typical individual being in the labor force.[1]

A. The Probabilities for the Reference Youths

Consider now the basic probabilities for the reference youth in the different age, race, and sex categories as reported in Table 1. It can be seen from the data in Column 7 that the probability of enrolling in school declines with age. The probability of enrolling in school is roughly the same for nonwhite and white males, and, other things the same, it is lower for white females than for nonwhite females.[2] With regard to labor force participation,

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[1] Among those who analyze a conditional distribution, it is not uncommon to do so simply by including enrollment status as an independent variable. This approach assumes that explanatory factors have the same impact on work activities by students and nonstudents. See, for example, Katz (1970).

[2] We should note that the same market-wide measure of job availability--a weighted average unemployment rate for all age, race, and sex groups--implies different levels of job availability for each group, especially for whites and nonwhites. The level of job availability for nonwhites associated with a given category of the unemployment measure we use is much lower than it is for whites. This can be seen in the following table.

Weeks Unemployed in 1975 as a Percent of Time in the Labor Force for Youth:

Averages for Cities Exhibiting High, Medium, and Low Unemployment

	White		Nonwhite	
	Male	Female	Male	Female
High U	0.175	0.145	0.319	0.254
Med U	0.142	0.094	0.264	0.259
Low U	0.101	0.071	0.225	0.193

Source: Survey of Income and Education

the rates shown in Column 8 are always higher for whites than for nonwhites and for males than females. Labor force participation increases with age except for a slight downturn for 21-22-year-old white females. From Columns 9 and 10 it can be seen that for males, labor force participation rates for those enrolled in school are always below participation rates for the not enrolled, while this is not always so for females.

One category of our dependent variable bears a special relation to a masure stressed by Bowen and Finegan. They were interested in what they called the activity rate--the ratio of those either in school or in the labor force to the total population. The activity rate is equal to one minus the probability of being observed in the not enrolled-not in labor force category. We report this latter probability in Column 4.

The probability of falling in the not enrolled, full-time in the labor force category increases with age for the four sex-race groups (Column 6). Nonwhite youth with reference level characteristics have a much lower probability of falling in the not enrolled, full-time in the labor force category than do comparable white youth. White males are, in comparison with all but younger nonwhite females, less likely than those in the other groups to be not enrolled, part-time in the labor force (Column 5). With the exception of older white males, the probability of falling in this category increases with age for all groups.

B. Effects of Variation in the Independent Variables

The following six tables report on the effects of variation in the basic family and labor market characteristics on the probability that a youth will fall within each of the work-schooling categories. Specifically, the numbers reported in each column are the differences in the respective probabilities if

TABLE 1

Probability of a Youth with "Reference" Characteristics Falling into the Indicated Labor Force-Schooling Category, by Age, Race, and Sex

	Enrolled in School			Not Enrolled								
	Not in Labor Force	In Labor Force <20 Weeks	In Labor Force >20 Weeks	Not in Labor Force <100 Hours	In Labor Force 100-1200 Hours	In Labor Force >1200 Hours	Probability of Enrollment (1)+(2)+(3)	Probability of Labor Force Participation (2)+(3)+(5)+(6)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)]	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
White Males												
17-18	.145	.320	.403	.021	.067	.045	.867	.835	.833	.846	.866	.876
19-20	.048	.164	.282	.027	.092	.388	.494	.926	.903	.947	.482	.642
21-22	.037	.127	.295	.030	.079	.434	.458	.934	.920	.945	.452	.550
Nonwhite Males												
17-18	.322	.297	.245	.038	.074	.025	.863	.641	.628	.726	.845	.896
19-20	.113	.193	.225	.079	.159	.231	.531	.808	.787	.832	.517	.590
21-22	.052	.082	.280	.029	.175	.382	.414	.919	.874	.950	.394	.643
White Females												
17-18	.246	.232	.316	.032	.105	.069	.794	.722	.690	.844	.759	.884
19-20	.051	.153	.185	.075	.198	.340	.388	.875	.870	.878	.386	.404
21-22	.038	.067	.157	.130	.214	.396	.261	.833	.854	.825	.268	.227
Nonwhite Females												
17-18	.359	.242	.252	.052	.060	.035	.853	.589	.580	.647	.837	.874
19-20	.112	.099	.303	.112	.177	.198	.513	.776	.782	.770	.517	.499
21-22	.072	.065	.210	.110	.205	.338	.347	.818	.793	.832	.337	.396

the characteristic under consideration alternately takes on the highest and lowest possible values. All other relevant independent variables are held at the level designated for the reference group. Note that the ΔG^2 statistic reported in Column 13 refers to all main and higher order effects, and tests for any relationship between the independent variable and the complete set of six outcomes for the dependent variable.

(1) Family Income. The first thing to notice is the effect of family income on the joint probability of enrolling and participating in the labor force (Columns 2 and 3) and of not enrolling but participating (Columns 5 and 6). Those with highest family income have a much higher joint probability of enrollment and participating and a much lower joint probability of being in the labor force and not in school than do those with lowest family income. As a result, it can be seen that, for all but younger white females, differences in family income have a bigger impact on the (marginal) probability of enrolling (Column 7) than on the (marginal) probability of participating in the labor force (Column 8). Indeed, while for other groups the probability of participating in the labor force is positively related to family income, it has virtually no relation for white males. The effect of family income on the probability of participating is smaller than the effect on enrollment because students who work part-time are counted in the labor force with equal weight with nonstudents who work full-time year-around. The strongest effect of family income is for youths who are 19 or older, whose schooling decisions pertain to levels of education beyond the customary minimum expected of all young people, and thus whose choices are not as constrained by social pressures as are the choices of 17- and 18-year-olds. Higher family income is also associated with a lower probability of being both not enrolled and not in the labor force (Column 4).

TABLE 2A

Differences in Probabilities between Those from Families with Highest and Lowest Incomes[a]

	Enrolled in School: Not in Labor Force (1)	Enrolled in School: In Labor Force ≤20 Weeks (2)	Enrolled in School: In Labor Force >20 Weeks (3)	Not Enrolled: Not in Labor Force <100 Hours (4)	Not Enrolled: In Labor Force 100-1200 Hours (5)	Not Enrolled: In Labor Force >1200 Hours (6)	Probability of Enrollment (1)+(2)+(3) (7)	Probability of Labor Force Participation (2)+(3)+(5)+(6) (8)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7) (9)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)] (10)	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8) (11)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)] (12)	ΔG^2[b] (Degrees of Freedom)
White Males													
17-18	.006	-.001	.048	-.010	-.018	-.024	.052	.004	.004	.025	.052	.054	174.4***
19-20	.014	.042	.092	-.009	-.007	-.132	.148	-.005	.004	.005	.148	.134	
21-22	.012	.037	.104	-.009	-.004	-.139	.153	-.003	.004	.005	.152	.153	(60)
Nonwhite Males													
17-18	-.075	.115	.084	-.035	-.075	-.014	.124	.110	.139	.050	.166	.073	38.2***
19-20	.006	.139	.155	-.065	-.138	-.097	.300	.059	.102	.053	.322	.245	
21-22	.008	.070	.232	-.023	-.145	-.143	.311	.015	.066	.019	.324	.221	(15)
White Females													
17-18	-.059	.075	.037	-.013	-.020	-.019	.053	.072	.091	.027	.075	.021	
19-20	-.007	.074	.044	-.025	-.021	-.065	.111	.032	.048	.020	.118	.056	51.0***
21-22	-.002	.040	.052	-.034	.007	-.048	.090	.037	.051	.026	.100	.043	(15)
Nonwhite Females													
17-18	.006	.026	.073	-.052	-.037	-.016	.105	.046	.044	-.024	.103	.104	
19-20	.038	.051	.179	-.094	-.098	-.076	.268	.056	.047	-.012	.275	.225	95.0***
21-22	.043	.055	.173	-.074	-.099	-.099	.272	.031	.046	-.006	.289	.215	(60)

[a] The highest family income category is greater than $25,000; the lowest one is less than $10,000. All other variables are held at their reference level.

[b] * indicates a significance level at 90% or above, ** at 95% or above, and *** at 99% or above. The level of significance refers to the joint significance of the main effect of the variable and any higher order interactions in which it may be involved. (Under the null hypothesis that the family income has no effect on the dependent variable, ΔG^2 has a χ^2 distribution with the indicated number of degrees of freedom.) The interaction between family income and family head's education is significant at the 95% level for white males and nonwhite females.

Test statistics, degrees of freedom, and significance levels for the age variable are as follows:

	ΔG^2	df	Significance
White Males	1372.9	50	99.5%
Nonwhite Males	415.9	10	99.5%
White Females	1921.6	70	99.5%
Nonwhite Females	407.7	10	99.5%

A positive relation between family income and time spent in the labor force might be the result of a number of factors--e.g., a relation between family income and the work ethic, the youth's preferences, and/or between family income and family connections, which make it easier to locate a job.[1] Note also the indication in Table 2A that the effect of family income on enrollment is much more pronounced for minority than for majority youth.[2] What happens to those young people who would be enrolled had they been from high income families, but who are not enrolled because their family incomes are low? An examination of Columns 4-6 indicates that for whites, these youths tend to be mostly in the labor force full-time; very few seem to fall into the part-time participation or nonparticipation categories. For nonwhites, however, the story is somewhat different. For them, almost equal numbers of youths from low income families end up in the part-time participation category as in the full-time participation category, and a substantial fraction go into the nonparticipation category.

In comparing the results of Table 2A to those from other studies, it should be remembered that the family income variable and the covered sample in our study are different from those of earlier ones. Specifically, our family income variable always refers to the income of the parents' family. Most earlier studies either used a combined measure of family income which referred to the parents' family if the youth lived at home or to the youth's, and perhaps the spouse's earnings if the youth lived away from home, or they confined the sample so that only those still living with their parents were included (as in

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[1] Bowen and Finegan, in examining the role played by family connections, found that young people whose parents are employed in sales occupations are more likely to be employed themselves. See, however, Rees and Gray (1979).

[2] In contrast, Lerman's (1972, p. 376) results suggest that family income had the same effect on enrollment for minority and for majority youth.

Bowen and Finegan's analysis of 14- to 17-year-old enrolled youth).

The conditional probabilities from our study indicate, first, that conditional on being enrolled in school, labor force participation is higher for those from families with highest incomes, but is only barely so for white males. Cohen, Rea, and Lerman applied ordinary least squares analysis to a sample consisting of 16- to 21-year-olds living in the 96 largest SMSA's. Their results and ours agree (see their Table G-11, which is most comparable).

Bowen and Finegan analyzed labor force participation for 18- to 24-year-olds enrolled in school. But they were not satisfied with the income variable and were suspicious of the results. For 14-17-year-olds enrolled, they find nonmonotonic effects of income. Labor force participation over part of the range increased with income. Eventually, however, participation for highest income youth fell below that for those in the lowest income classes. While our full results pertaining to the variation of participation with each of the four income categories are not reported here, only for enrolled white males do we find a nonmonotonic pattern similar to the one reported in Bowen and Finegan.

Our calculations of labor force participation rates conditional on nonenrollment status are presented in Column 10. Bowen and Finegan find no important impact of family income for this group (p. 415), which is the way we would characterize the results for white males. However, Cohen, Rea, and Lerman find a negative impact on participation (Table G-11).

Our findings in Columns 11 and 12 point to strong positive effects of family income on school enrollment for those in the labor force and for those out of it. Lerman finds similar strong positive effects. However, Lerman's findings also indicate that differences in family income have a somewhat larger impact on enrollment for those out of the labor force than for those in it. If anything, our findings point slightly in the other direction.

(ii) Family Head's Education. Table 2B presents the estimates of the effects of differences in the education of the family head on the various labor force participation and enrollment categories. Increases in the family head's education have a strong positive impact on the probability of enrollment for all age, race, and sex groups. There is for 17-18-year-olds a positive impact on labor force participation as well. But for the older groups the effects of higher levels of parental education on participation is mixed. For nonwhite females, Table 2B indicates that the probability of being not enrolled/part-time in the labor force and the probability of being enrolled and in the labor force more than 20 weeks are particularly sensitive to variations in the head's education.

For those in the labor force, enrollment probabilities increase with the head's education. Given the mixed results for those not in the labor force, our findings concur with Lerman's observation that the head's education is more likely to be associated with school enrollment for those in the labor force than for those outside it.

(iii) Number of Parents Home. As can be seen from Table 2C, the variable measuring whether there are one or two parents home is significant at better than the 95 percent level only for males. In general, the effects on the probabilities of enrollment and of labor force participation vary in sign among groups. The same is true of the measures referring to the probability of different amounts of hours worked.

(iv) Head Employed. Family head's employment status is included to control for the added worker effect. It does not have a significant impact for males. The impact for white females is significant at better than the 95 percent level, while for nonwhite females it is significant only at somewhat more

TABLE 2B

Differences in Probabilities between Those Whose Family Head's Education Is in the Highest and Lowest Categories[a]

	Enrolled in School: Not in Labor Force	Enrolled in School: In Labor Force <20 Weeks	Enrolled in School: In Labor Force >20 Weeks	Not Enrolled: Not in Labor Force <100 Hours	Not Enrolled: In Labor Force 100-1200 Hours	Not Enrolled: In Labor Force >1200 Hours	Probability of Enrollment (1)+(2)+(3)	Probability of Labor Force Participation (2)+(3)+(5)+(6)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)]	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)]	ΔG^2[b] (Degrees of Freedom)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
White Males													
17-18	-.012	-.002	.168	-.028	-.041	-.046	.114	.040	.037	.036	.112	.121	
19-20	-.001	.170	.122	-.003	-.070	-.217	.290	.005	.049	-.032	.311	.023	409.1***
21-22	.013	.045	.064	.002	-.009	-.115	.123	-.015	-.010	-.013	.123	.092	(90)
Nonwhite Males													
17-18	-.035	.046	.023	.004	-.023	-.015	.034	.031	.054	-.120	.066	-.019	
19-20	.005	.062	.053	.020	-.032	-.109	.121	-.025	.038	-.098	.162	-.050	18.6
21-22	.009	.038	.101	.011	-.019	-.140	.148	-.020	.025	-.035	.161	-.048	(15)
White Females													
17-18	.055	.082	.072	-.060	-.083	-.066	.209	.006	.019	.141	.219	.189	
19-20	.017	.206	.071	-.026	-.087	-.182	.295	.009	.090	-.030	.325	.137	304.7***
21-22	.023	.081	.053	-.019	-.024	-.114	.157	-.004	-.001	-.012	.165	.123	(45)
Nonwhite Females													
17-18	-.079	.059	.143	-.054	-.053	-.016	.122	.133	.143	-.091	.136	.088	
19-20	-.003	.056	.270	-.100	-.151	-.072	.323	.103	.110	.047	.345	.183	118.6***
21-22	.014	.060	.261	-.080	-.166	-.088	.334	.067	.107	-.023	.371	.172	(60)

[a] In calculating these differences in probabilities, the probability for a youth whose family head's education is less than a high school graduate is subtracted from the probability for a youth whose family head's education is at least a college graduate. All other variables except age are held at their reference level.

[b] See footnote to Table 2A for explanation. The interaction with family income is significant at the 95% level for white males and nonwhite females, and the interaction with age is significant for white males and white females.

TABLE 2C

Differences in Probabilities between Young People with One Parent vs. Both Parents Home[a]

	Enrolled in School			Not Enrolled									
	Not in Labor Force	In Labor Force <20 Weeks	In Labor Force >20 Weeks	Not in Labor Force <100 Hours	In Labor Force 100-1200 Hours	In Labor Force >1200 Hours	Probability of Enrollment (1)+(2)+(3)	Probability of Labor Force Participation (2)+(3)+(5)+(6)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)]	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)]	ΔG^2[b] (Degrees of Freedom)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
White Males													
17-18	-.005	.051	-.069	-.002	.014	.010	-.022	.007	.001	.037	-.028	.009	40.8***
19-20	.014	-.058	.052	.004	.061	-.073	.008	-.018	-.026	-.008	.003	.029	
21-22	-.006	.055	-.037	-.015	.007	-.004	.012	.021	.016	.026	.009	.113	(15)
Nonwhite Males													
17-18	-.093	.069	-.021	.029	.011	.004	-.044	.063	.093	-.095	-.008	-.121	12.3**
19-20	-.041	.020	-.041	.047	.003	.012	-.063	-.006	.059	-.068	-.023	-.225	
21-22	-.018	.010	-.047	.018	.007	-.029	-.055	0	.032	-.024	-.040	-.225	(5)
White Females													
17-18	.023	.005	-.015	.003	-.008	-.008	.013	-.026	-.024	-.025	.013	.000	
19-20	.007	.011	.000	.011	-.006	-.024	.018	-.018	-.013	-.022	.021	.000	16.6*
21-22	.006	.005	.000	.020	-.005	-.026	.011	-.025	-.015	-.030	.015	.000	(10)
Nonwhite Females													
17-18	-.062	.039	.025	-.004	.004	-.001	.001	.066	.073	.023	.013	-.013	
19-20	-.021	.013	.023	-.011	.006	-.011	.015	.032	.046	.015	.024	-.028	3.7
21-22	-.013	.010	.018	-.009	.010	-.015	.014	.022	.045	.011	.024	-.027	(5)

[a] Probability with one parent home minus probability with two parents home.

[b] See footnote to Table 2A for explanation. The interaction with age is significant at the 95% level for white males, and the interaction with the head's employment status is significant at the same level for white females.

TABLE 2D

Differences in Probability and Family Head's Employment Status[a]

	Enrolled in School				Not Enrolled								
	Not in Labor Force (1)	In Labor Force <20 Weeks (2)	In Labor Force >20 Weeks (3)	Not in Labor Force <100 Hours (4)	In Labor Force 100-1200 Hours (5)	In Labor Force >1200 Hours (6)	Probability of Enrollment (1)+(2)+(3) (7)	Probability of Labor Force Participation (2)+(3)+(5)+(6) (8)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7) (9)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)] (10)	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8) (11)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)] (12)	ΔG^2 [b] (Degrees of Freedom)
White Males													
17-18	.006	-.006	-.003	-.008	.012	-.001	-.003	.002	-.007	.062	-.013	.047	
19-20	.002	-.002	0	-.010	.017	-.007	0	.008	-.004	.020	-.006	.110	4.5
21-22	.002	-.001	.001	-.011	.015	-.006	.002	.009	-.004	.021	-.004	.124	(5)
Nonwhite Males													
17-18	-.008	-.050	.063	-.001	-.006	.002	.005	.009	.011	-.003	.008	0	
19-20	-.005	-.036	.052	-.004	-.015	.009	.010	.009	.014	.005	.013	0	3.5
21-22	-.005	-.018	.050	-.003	-.026	-.001	.027	.007	.018	.002	.031	0	(5)
White Females													
17-18	.010	-.051	.003	.011	.014	.013	-.038	-.021	-.029	-.021	-.045	-.029	
19-20	-.002	-.043	-.013	.018	.008	.033	-.058	-.016	-.016	-.016	-.058	-.060	19.9**
21-22	-.003	-.021	-.017	.024	-.001	.019	-.041	-.020	-.013	-.021	-.040	-.042	(10)
Nonwhite Females													
17-18	-.011	.054	-.080	.006	.023	.008	-.037	.005	-.006	.040	-.051	-.016	
19-20	-.009	.016	-.106	.006	.056	.036	-.098	.002	-.031	.028	-.117	-.034	9.2*
21-22	-.010	.006	-.082	-.001	.049	.037	-.085	.010	-.031	.020	-.096	-.032	(5)

[a] Probability if head is unemployed minus probability if head is employed.

[b] See footnote to Table 2A for explanation. The interaction with the number of parents present is significant at the 95% level for white females.

than the 90 percent level. Both groups of females are less likely to be enrolled if the family head is unemployed. And while the effect on overall labor force participation differs between the two groups, it can be seen from Column 6 that the probability of not enrolling and participating full-time in the labor force is consistently higher for those young women whose family head is unemployed. This is clearly what the added worker hypothesis would lead us to expect, but again, it is not of importance for young men.[1]

Bowen and Finegan's (pp. 399-401) findings indicate some statistically insignificant added worker effects for 14-17-year-old girls enrolled in school, and for 18-24-year-old young men who are not enrolled but still live at home. For 14-17-year-old boys still enrolled, if the father is unemployed, they find a <u>significant</u> <u>negative</u> effect on labor force participation. Our results with respect to this variable are weak, and age categories do not correspond fully to theirs. Nothing in our findings strongly contradicts their results.

Mincer (1966, p. 95) argues that, given a lower relative asset position of poorer families, he expects that added workers are more likely to come from lower income families. There is no significant interaction between family income and head's unemployment to indicate that the impact of head's unemployment varies with family income. It is important to note, however, that the inclusion of those who have left home in the sample may have weakened the effect of the <u>head</u> <u>of</u> <u>parents'</u> <u>household</u> employed measure. To be sure, those who have left home may increase their work effort if the head of their parents' household is unemployed--e.g., they may wish to help out even though they aren't living at home, or they may be forced to support themselves if they had been receiving transfers from their parents. But it seems reasonable to expect

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[1] A portion of the added worker effect may be captured by the family income variable, thus weakening the measured impact of parental unemployment.

that a youth living away from home is probably less likely to adjust his or her own employment status in light of the parents' circumstances than is a youth who still lives at home. Despite this expectation, we find the effect of a difference in parental employment status is significant for young women, who are more likely to have left home, while it is not for young men. This may reflect a stronger family commitment to the education of the young men.

(v) Wages. Table 2E reports the effects on the probabilities of falling in each of the school-work categories of a difference in the observed wage from less than 27 percent of the average adult wage to greater than 63 percent of the adult wage. In other words, this table represents the response of the youth to a more than doubling of his or her wage rate. This effect is statistically significant for all but nonwhite females.

The probability of enrollment is lower for those in the highest compared to the lowest wage category. The negative impact is greater in absolute terms for 19-22-year-olds than for those 17-18 and is greater for males than it is for females. The probability of labor force participation increases with the wage for all but younger white females.

The relatively weak effects on the overall participation rate are accompanied by major differences in the probability of putting longer time in the labor force. These do not result in large changes in the labor force participation rate because the higher probability of working longer hours if a high wage is offered is accompanied by a lower probability of falling in the part-time in the labor force categories.

These findings may be questioned on a number of grounds. Most importantly, a question can be raised as to whether the finding that hours supplied increase with the wage inadvertently reflects a relationship running from hours to wages--i.e., firms offer higher wages for full-time than for part-

TABLE 2E

Differences in Probabilities between Youth with Highest and Lowest Relative Wages[a]

	Enrolled in School			Not Enrolled									
	Not in Labor Force (1)	In Labor Force <20 Weeks (2)	In Labor Force >20 Weeks (3)	Not in Labor Force <100 Hours (4)	In Labor Force 100-1200 Hours (5)	In Labor Force >1200 Hours (6)	Probability of Enrollment (1)+(2)+(3) (7)	Probability of Labor Force Participation (2)+(3)+(5)+(6) (8)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7) (9)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)] (10)	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8) (11)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)] (12)	ΔG^2[b] (Degrees of Freedom)
White Males													
17-18	-.005	-.049	-.031	.014	.026	.045	-.085	-.009	-.012	.001	-.088	-.072	125.2***
19-20	-.018	-.070	-.112	.006	.001	.192	-.199	.012	-.007	.009	-.202	-.139	
21-22	-.015	-.057	-.126	.005	-.002	.194	-.198	.009	-.005	.010	-.200	-.145	(15)
Nonwhite Males													
17-18	-.018	-.091	.047	.012	.022	.028	-.062	.007	-.006	.029	-.076	-.035	33.8***
19-20	-.034	-.097	-.026	.001	-.002	.159	-.158	.034	.004	.048	-.170	-.085	
21-22	-.022	-.050	-.076	-.004	-.030	.182	-.148	.027	.014	.018	-.147	-.082	(15)
White Females													
17-18	-.013	.050	-.055	.016	.047	-.045	-.018	-.003	.009	-.072	-.003	-.054	
19-20	.001	-.050	-.028	.010	.002	.065	-.077	-.011	-.024	.002	-.084	-.023	161.42***
21-22	-.004	-.038	-.004	-.023	-.108	.169	-.038	.027	-.005	.039	-.049	.012	(45)
Nonwhite Females													
17-18	-.053	-.006	.038	.010	-.018	.028	-.021	.042	.053	-.025	-.006	-.044	
19-20	-.029	-.016	-.007	.007	-.076	.120	-.052	.023	.038	.009	-.042	-.095	21.0
21-22	-.024	-.016	-.026	-.002	-.106	.174	-.066	.027	.037	.019	-.060	-.090	(15)

[a] In calculating these differences in probabilities, the independent variable takes on the lowest value if the youth's wage is less than 27% of the average adult wage and the highest value if the youth's wage is greater than 63% of the adult wage. All other variables except age are held at their reference level.

[b] See footnote to Table 2A for explanation. The interaction with age is significant at the 95% level for white females.

time work.[1] While theoretically, the market relation between wage rates and time spent at work (which Rosen [1976] calls the wage-hours locus) may be positively or negatively sloped, the available empirical literature suggests a positive relationship (see Lazear, 1977; Owen, 1978; Parsons, 1974; and Rosen, 1976).[2]

A number of approaches may be taken to correct for the potential bias arising from the influence of the wage-hours locus. Essentially, we can try to calculate the wage that would be offered to each individual at a constant amount of work, thus eliminating the correlation between wages and hours that would result from movement along the wage-hours locus. One approach is to substitute for the actual wage for full-time workers the wage distribution for part-time workers of the same age and sex who work in the same city where the full-time workers live and to estimate the results for the four race-sex groups using the calculated part-time wage distribution for those with full-time earnings. When such estimates are made, we find that the level of significance for the wage variable falls to just below 95 percent for white males and just below 90 percent for nonwhite males. The wage variable becomes insignificant for white females and had previously been found to be insignificant for nonwhite

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[1] We should take note of other potential sources of bias which may lead to an underestimate of the effect of wages on hours supplied. First, earnings may be measured with error. Second, the amount of time employed may be measured with error, causing the denominator of the wage variable to be related to the value of the dependent variable. A standard approach for dealing with errors in measurement is to use instrumental variables. However, many of the instruments normally used--age, race, sex, residence in a city--already form the basis for dividing our sample into subgroups. Those pertaining to education are inappropriate because they may be endogenously related to the dependent variable. Third, there is also evidence that part-time work may be easier to do than full-time work (Lazear, 1977), with the result that unmeasured nonpecuniary benefits may be negatively related to the wage rate.

[2] It may be argued, however, that some of the evidence suggesting a positively sloped wage-hours relationship merely reflects the existence of a positively sloped labor supply curve.

females.[1] Comparing the results for males in Columns 6(a), 7(a), and 8(a) of

Differences in Probabilities between Youth
with Highest and Lowest Relative Wages--
Estimated Part-Time Wage Used for Those Who Work Full-Time

	Not Enrolled, In Labor Force >1200 Hours (6)		Probability of Enrollment (7)		Probability of Labor Force Participation (8)	
	(a)	(b)	(a)	(b)	(a)	(b)
White Males						
17-18	.006	-.002	-.046	-.048	.006	.006
19-20	.015	-.021	-.053	-.040	-.002	-.007
21-22	.013	-.014	-.046	-.039	-.006	-.011
Nonwhite Males						
17-18	.006	-	-.033	-	.016	-
19-20	.029	-	-.057	-	.018	-
21-22	.015	-	-.028	-	.013	-

the above table with the analogous figures in Table 2E, we find that while the impact of substantial wage differences on the probability of labor force participation is very small whichever procedure is used, the magnitude of the effect of wages on enrollment probability and on the probability of being not enrolled in the labor force more than 1200 hours are both reduced dramatically when estimated part-time wages are used instead of actual full-time wages. These findings are consistent with a view that the estimates reported in Table 2E may have been influenced, at least in part, by a positively sloping wage-hours locus. On the other hand, based on these results alone, we cannot be sure that the impact of wages on the allocation of time is as small as the results using the part-time wage instrument indicate. The available instrument for this procedure was the identity of the SMSA in which the person worked, but this instrument accounts for only 8 to 14 percent of the variance of the re-

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[1] The measured impacts of the other independent variables are not changed in any important way by this procedure.

corded part-time wages.

Therefore, to provide a further check on our findings, we modify the estimating procedure to take into account Rosen's findings as to the estimated slope of the wage-hours locus for women. According to his findings, the wage increases by 2 percent for each additional 100 hours supplied. We proceed by recalculating wage rates for all observations assuming 1000 hours worked. Thus, if an individual worked 2000 hours, we used a calculated wage that was 20 percent below the wage rate actually observed. A problem with this procedure is that we do not know what the wage-hour locus really looks like. It may, for example, be discontinuous with part-time work during the summer paid at a different rate from part-time work during the year.[1] Thus, estimates for youth based on Rosen's findings for women should be viewed with great caution.[2] If one had full knowledge of the wage-hours locus it would be appropriate to calculate and use the marginal return to work in the labor supply curve. We use only the calculated wage. Results for white males are reported in Columns 6(b), 7(b), and 8(b) of the preceding table. The wage variable is significant at above the 99 percent level for white males, but is not significantly different from zero at any standard level for nonwhite males. The only wage effect that persists for estimates in Table 2E and those reported above is that higher wages reduce the probability of enrollment.[3] These results imply that

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[1] Over some range, it is conceivable that the wage rate varies inversely with hours worked. E.g., the wage rate paid for summer work may exceed that paid for an after-school job.

[2] We should also note that Rosen's estimates themselves may be subject to wide error, even when applied to women. One reason is the choice of which instruments appear in the wage-hours locus and which appear in the labor supply curve are subject to question. E.g., education appears in the wage-hours locus, but not the labor supply curve.

[3] Even this finding does not hold up if it is assumed that the true slope of the wage-hours locus reflects a 3 percent wage increase for every additional 100 hours worked.

estimated wage elasticities of enrollment and of labor supply are very sensitive to assumptions about the wage-hours locus. Since we do not have very good information on what it looks like, extreme caution should be exercised before assuming coefficients estimated for the wage variable represent the true parameter values of the labor supply curve.

(vi) Area Unemployment Rate for Youth. The area unemployment rate for youth is included to test for the effects of interarea differences in job availability on enrollment and labor supply. Since the wage is also included as an independent variable, a finding that the relation between job availability and time supplied to various activities is significant will mean that job availability has a truly independent impact. This was not clear from previous studies, which did not include the wage as an independent determinant of the quantity of labor supplied. The reason is that in these earlier studies, the measures of job availability, reflecting as they do the demand for labor, may have acted as a surrogate for the wage. It can be seen from our findings in Table 2F, however, that even when wages are included as a separate explanatory variable, youth unemployment has an impact that is significant at better than the 95 percent level for three of the four groups considered.[1] The exception is white females.

In areas with low youth unemployment rates vis-a-vis those with high rates, the probability of enrolling in school is lower for white males, nonwhite males, and white females. Bowen and Finegan (p. 450) found, in general agreement with our results, that higher area unemployment raises the probability of enrollment for males. With the exception of a slight negative ef-

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[1] The estimated impact of unemployment is changed only slightly when instruments for part-time wages, or calculated wages assuming a 2 percent increase for every 100 hours supplied, are substituted for full-time wages.

TABLE 2F

Differences in Probabilities between Youth Living in Areas
with Lowest and Highest Youth Unemployment Rates

	Enrolled in School			Not Enrolled									
	Not in Labor Force (1)	In Labor Force <20 Weeks (2)	In Labor Force >20 Weeks (3)	Not in Labor Force <100 Hours (4)	In Labor Force 100-1200 Hours (5)	In Labor Force >1200 Hours (6)	Probability of Enrollment (1)+(2)+(3) (7)	Probability of Labor Force Participation (2)+(3)+(5)+(6) (8)	Labor Force Participation Conditional on Enrollment [(2)+(3)]÷(7) (9)	Labor Force Participation Conditional on Nonenrollment [(5)+(6)]÷[1-(7)] (10)	Enrollment Condtl. on Labor Force Participation [(2)+(3)]÷(8) (11)	Enrollment Condtl. on Not in Labor Force (1)÷[1-(8)] (12)	ΔG^2 [a] (Degrees of Freedom)
White Males													
17-18	-.035	.019	.009	.012	-.011	.006	-.007	.023	.039	-.073	.010	-.081	
19-20	-.014	.001	-.008	.013	-.019	.027	-.021	.001	.025	-.023	-.008	-.166	22.1***
21-22	-.011	0	-.011	.015	-.017	.026	-.023	-.004	.021	-.023	-.011	-.177	(30)
Nonwhite Males													
17-18	-.007	.041	-.036	-.010	-.002	.012	-.001	.016	.007	.079	-.013	.023	
19-20	-.013	.006	-.051	-.029	-.017	.104	-.058	.042	.001	.091	-.086	.058	19.9**
21-22	-.011	-.007	-.089	-.014	-.035	.155	-.107	.025	-.008	.036	-.117	.055	(10)
White Females													
17-18	-.033	.016	.008	.001	.006	.002	-.010	.032	.038	.001	.000	-.018	
19-20	-.008	.006	-.002	.000	.004	.000	-.005	.008	.021	.000	.001	-.041	4.9
21-22	-.006	.002	-.001	.001	.004	.000	-.005	.006	.022	.000	.000	-.030	(10)
Nonwhite Females													
17-18	-.048	.007	.049	-.005	-.007	.005	.008	.054	.059	.020	.018	-.001	
19-20	-.025	-.004	.057	-.020	-.034	.024	.029	.044	.063	.025	.043	-.002	23.0**
21-22	-.017	-.003	.040	-.020	-.041	.041	.020	.037	.063	.025	.032	-.002	(10)

[a] See footnote to Table 2A for explanation.

fect for older white males, the probability of labor force participation is higher in areas where jobs are more readily available.

Bowen and Finegan have set forth an argument that jobs are likely to be particularly important for minority youth so that they could help finance their way through school. The response of nonwhite women to greater job availability is consistent with this view. Enrollment and labor force participation rates are higher in areas with lower unemployment. Nonwhite men, however, appear to take advantage of readily available jobs by leaving school to begin working on a full-time basis. For these men, the increase in the not enrolled/full-time participation is very substantial, amounting to 40 to 48 percent of the reference probabilities of falling in this category (see Table 1).

Bowen and Finegan found, before correcting their results for the effects of those who shift employment status, that labor force participation for those not enrolled responded more to differences in job availability than did labor force participation for those enrolled (p. 424). Similarly, Cohen, Rea, and Lerman found lower unemployment associated with greater labor force participation for those not enrolled, with the same relationship holding weakly between areas with the highest and lowest unemployment rates for those enrolled. With regard to the probability of enrollment conditional on participation, Lerman found for those in the labor force, higher unemployment is associated with greater school participation, while for those not in the labor force, he found no significant effect of unemployment on enrollment. In general, our results for the various conditional probabilities, as presented in Columns 9 through 12 of Table 2F, are mixed. They tend to support the findings of the other studies cited for some sex-race categories, but not for others.

IV. Summary and Implications

This study has used a relatively new statistical technique, discrete multivariate analysis, to estimate in a simultaneous framework the effects of family background and labor market conditions on the enrollment choices by youth and on the time they supply to the labor market. Where possible, findings have been compared to those from earlier studies, with similarities and differences pointed out.

Parental income and the education of the head of the family have much stronger effects than either the number of parents living at home or the head's employment status. Added worker effects are found for young women but not for young men.

No matter what wage measure is used, higher relative wage offers seem to reduce the probability of the youth enrolling in school, but the size of the estimated impact of wage on enrollment, and the impact on labor supply are very sensitive to whether or not adjustments are made for the possibility that wage rate offers by firms are higher for full-time than for part-time work. If estimates of labor supply curves obtained by others, especially for secondary workers, are as sensitive to the treatment of the wage variable as our results indicate they are, great caution and a clear awareness of the potential variance in estimated results is called for before applying them to the design of public policy programs.

Job availability, as measured by youth unemployment, does seem to influence youth labor supply, with the strongest effect on the labor supply for nonwhite males. The results suggest that nonwhite males in low unemployment areas will be in the labor force full-time 40 to almost 50 percent more often than will similar males in high unemployment areas. Moreover, since a wage measure is included as an independent variable, we can be sure that the job availability measure is not acting as a surrogate for an absent wage variable, but instead has an impact of its own.

Youth-oriented labor market experiments have been proposed and conducted in the past, and some are in progress (e.g., the Youth Entitlement Incentive Pilot Project). Income and substitution effects of the changes brought about by these programs may be calculated and used to make projections of program impact. Our findings suggest that job availability may play a direct role in influencing the budget constraint facing the youth. Accordingly, explicit consideration should be given to the role of job availability when calculating income and substitution effects, and in making national projections based on results pertaining to a particular site.

Further developments along the lines pursued here may make it easier to estimate the impact of interarea or intertemporal differences in market conditions on school enrollment and youth labor supply. This may be especially helpful in evaluating experiments which implement different school or job programs in different cities. Results such as those developed in this paper can aid in separating out that part of the outcomes of these programs (e.g., dropout rates or school continuation rates) due to the impact of the program from that part which arises merely because market conditions vary among the various cities in which the experiment is being conducted. Moreover, in the case of experiments like the Youth Entitlement Project, which saturate the labor market with jobs for young people, there is a special need to estimate, based on information from outside of the experiment, what enrollment and labor supply would have been in the absence of the program.

The supply curve we have estimated constitutes one of the structural equations in a model of the effects of the minimum wage on youth labor market activities and enrollment behavior.[1] In concluding, it is appropriate to note that while our findings are consistent with a view that minimum wages discourage labor market activity and increase school enrollment, they are not themselves sufficient to generate such a result.

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[1] The likely importance of job rationing in a model of the impact of minimum wages has been recognized by Welch (1974), Mincer (1976), Gramlich (1976), and others. Interactions between school and work and their implications for the measured impact of the minimum wage have been examined by Ehrenberg and Marcus (1979), Leighton and Mincer (1979), and Mattila (1978).

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