The Benefit of Additional High School Math and Science Classes
For Young Men and Women

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ABSTRACT

This paper examines the effects of taking more high school math and science classes on wages, the likelihood of entering a technical job or a job traditional for one's sex, and the likelihood of choosing a technical college major or a major traditional for one's sex. Results from two data sets show that taking more high school math increases wages and increases the likelihood of entering technical and nontraditional fields for female college graduates. No significant impact from taking more high school math is consistently observed for other workers and high school science courses have little effect on these outcomes.

KEYWORDS

Returns to Education

Technical Training

High School Curriculum

Human Capital

1. INTRODUCTION

Labor force projections for the coming decade, including those made in the influential book, Workforce 2000 (Johnston and Packer, 1987), indicate that growth in employment demand will be concentrated in the highly skilled service sector. Employment in occupations such as "Natural, Computer, and Mathematical Scientists" and "Health Diagnosing and Treating Occupations" is expected to increase by more than 50 percent by the year 2000. The same projections indicate that workers without technical (i.e. mathematical and scientific) skills will be left behind by an economy increasingly demanding these skills.

These projections have additional implications for future trends in the wage gap between men and women. Traditionally, women acquire less technical training (c.f. Sherman and Fennema, 1977) and are less likely to choose technical careers (c.f. Reskin and Hartmann, 1986) than men. Differences in the level of training in math and the sciences may therefore contribute to the wage gap between men and women. In fact, one study shows that, even though women earn roughly 70% of what men earn, women without children who have taken at least eight college credits in math and science earn approximately the same as equally educated men (Adelman, 1991). If women's training patterns persist and labor demand shifts towards more technical fields, one could project a growing wage differential between men and women.

In addition, American students perform worse than their peers in other industrialized countries on standardized exams of math and science. A recent compilation of international comparisons in student math and science exam scores shows that Americans are at or near the bottom in virtually every exam administered (Digest of Education Statistics, 1991). If the skills learned in these subjects are positively related to a worker's productivity, then American firms may be at a competitive disadvantage as these students enter the workforce.

These circumstances suggest that the educational system should encourage students, and particularly girls, to increase their technical training by taking more math and science courses in school. Intervention at the high school level, in particular, may be advantageous for two reasons. First, states largely control the curriculum and services provided to high school students and intervention at this level would be considerably easier than at the college level. Second, since about half of high school students do not go on to college, more students would be exposed to the potential benefits if the additional training occurred at the high school level.

Evidence of the benefits of taking more math and science in high school, however, is limited. The existing literature provides surprisingly little evidence on the returns to different components of the high school curriculum aside from vocational training (Altonji 1992; Rumberger and Daymont 1984, are exceptions) and no studies that we know of differentiate returns by gender. The purpose of this paper is to fill in some of this gap by examining the effects of more technical training in high school on educational and labor market outcomes for men and women. We examine whether taking more high school math and science classes leads to higher subsequent labor market earnings. Since earnings are affected by educational and occupational choices, we also consider the effect of technical curriculum on an individual's propensity to obtain employment in a technical occupation or in an occupation traditional for one's gender, the likelihood of continuing on to, and graduating from, college, and the likelihood that college graduates choose majors which are technical or traditional for one's gender.

We use two data sources, the National Longitudinal Survey of Youth (NLSY) and the 1980 cohort of High School and Beyond (HSB), to examine these issues. Our findings from both data sets consistently indicate that additional high school math classes have an effect on educational and labor market outcomes for female college graduates. Results for other groups of workers are less consistent regarding the effects of taking more high school math. On the

other hand, high school science classes appear to have very little impact on most of the outcome measures considered here for both men and women in both data sets.

2. METHODOLOGY

This section of the paper discusses the models estimated and the potential econometric problems inherent in these models. Since we are interested in different outcome measures, several models will be estimated. For the purposes of brevity and simplicity of notation, however, we restrict the formal model specification and the discussion of potential econometric problems to the wage models. Extensions to the other outcome measures are straightforward.

To examine the effect that additional math and science courses would have on a worker's wage we estimate OLS regression models of the form:

$$\begin{aligned} \ln W_i &= X_i\beta_{1g} + F_i\beta_{2g} + C_i\beta_{3g} + e_i \quad ; \\ i &= 1, \dots, N_g ; \quad g = 1, 2 \end{aligned} \quad (1)$$

$$\begin{aligned} \ln W_i &= X_i\beta_{1gj} + F_i\beta_{2gj} + C_i\beta_{3gj} + e_i \quad ; \\ i &= 1, \dots, N_{gj} ; \quad j = 1, \dots, 3 ; \quad ; \quad g = 1, 2 \end{aligned} \quad (2)$$

where $\ln W_i$ is the natural log of wages, X_i is a vector of observed individual characteristics, such as education, age, and marital status, F_i is a vector of family background characteristics, such as parents' education or number of siblings, C_i reflects the number of courses taken separately in math and science, i indexes individuals, g indexes gender, j indexes levels of educational attainment (high school graduate, some college, or college graduate; workers who have not graduated from high school are not included in the analysis as discussed below) and N represents the number of respondents in each gender/educational attainment group. The vectors of

estimated slope coefficients, $\hat{\alpha}_3$, would then provide a ceteris paribus estimate of the effect of taking one extra math or science class on the log wage.

There are econometric problems inherent in estimating models of the forms specified in equations (1) and (2), many of which have been discussed at length in Altonji (1992). The underlying difficulty is the possibility that relevant characteristics have been excluded from these equations leading to biased estimates of β_3 , the vector of curriculum coefficients. If, for example, an individual's ability affects her earnings but no measure of ability is included in the regression equation, then, if more able workers take more math and science courses, the estimate for β_3 will be biased upward. More formally, an alternative specification of equation (1) or (2) may take the form:

$$\ln W_i = X_i\alpha_1 + F_i\alpha_2 + C_i\alpha_3 + A_i\alpha_4 + u_i \quad ; \quad (3)$$

where A_i represents unobserved ability that influences wages and all other notation is the same as above. Subgroup subscripts are dropped here and for the remainder of the discussion for convenience. If $\alpha_4 > 0$ and $\text{cov}(C_i, A_i) > 0$, then $\hat{\alpha}_3$ will be biased upward.

To control for this source of bias as best we are able, we employ extensive measures for all three categories of explanatory variables expressed in equations (1) and (2). An additional set of explanatory variables which we consider to control for these unobservable differences is a vector of test scores which are intended to measure an individual's aptitude in different areas, including math and science. In this case, the model that we estimate is:

$$\ln W_i = X_i\beta_1 + F_i\beta_2 + C_i\beta_3 + S_i\beta_4 + e_i \quad ; \quad (4)$$

where S_i represents an individual's test score and all other notation is as above. This approach is also used by Altonji (1992), Kane and Rouse (1993), and Blackburn and Neumark (1993), among others. Test scores may proxy technical ability and help reduce the upward bias created

by unobservable characteristics. Including these test scores, however, poses additional problems (see Griliches, 1977). First, it is possible that students who take more math and science classes learn material which can be used to improve their performance on standardized exams. More formally, a model of test performance may take the form:

$$S_i = X_i\gamma_1 + F_i\gamma_2 + C_i\gamma_3 + A_i\gamma_4 + v_i. \quad (5)$$

Treating the coefficients as scalars and solving for A_i in (5), then substituting into (3) yields:

$$\begin{aligned} \ln W_i = & X_i(\alpha_1 - \alpha_4\gamma_1/\gamma_4) + F_i(\alpha_2 - \alpha_4\gamma_2/\gamma_4) + C_i(\alpha_3 - \alpha_4\gamma_3/\gamma_4) \\ & + S_i(\alpha_4/\gamma_4) + [u_i - (\alpha_4/\gamma_4)v_i] \quad ; \end{aligned} \quad (6)$$

which has the form of equation (4). The coefficient, β_3 , will equal the true effect of curriculum on wages, α_3 , if curriculum has no impact on test scores, *ceteris paribus* ($\gamma_3 = 0$), or if the observed personal characteristics perfectly control for differences in ability ($\alpha_4 = 0$). If $\gamma_3 > 0$ and $\alpha_4 > 0$, however, a negative bias will be imposed upon $\hat{\alpha}_3$. Second, OLS estimates of β_3 will be negatively biased because the error term in equation (4) is negatively correlated with S_i . While an instrumental variable procedure could correct this problem, no instruments valid for this purpose are readily available. To examine the sensitivity of the results to these potential problems, we discuss the results of estimating equations (1) and (2) with and without controlling for test scores.

Another technique to control for the bias introduced by unobservable characteristics is to employ an instrumental variable procedure. Using this approach, variables correlated with curriculum but uncorrelated with the errors in the outcome equations are used as instruments for the curriculum variables. Altonji (1992) has done this using the mean number of courses taken in each subject in the respondent's high school as the instruments in his analysis of the returns to high school curriculum. As Altonji points out, however, such variables are not ideal

instruments because high school means may proxy things like unobservable family background characteristics or school quality that are related to subsequent wages.

The format of the HSB data allows us to apply Altonji's approach here (high school identifiers needed to estimate the mean number of classes taken within a high school are not available in the NLSY). As reported below, we find results which are not statistically significantly different from the OLS estimates primarily because of the large standard errors on the estimated IV coefficients. Altonji obtained similar results. We have also tried other variables as potential instruments such as the demographic composition of the students and faculty in a respondent's school, and state graduation requirements. In all of our findings these instruments appear to be inadequate as parameter estimates become wildly imprecise. Without obvious alternative instruments that could provide more precise estimates, this technique cannot adequately address the biases present here.

Using data on siblings is yet another approach that could be applied to correct the potential problems created by omitted personal characteristics. (for other applications of this approach, see Ashenfelter and Krueger 1992; or Ashenfelter and Zimmerman 1993). For instance, equation (3) may be modified to represent the wages of two siblings, i and k . If omitted personal characteristics are equivalent within families ($A_i = A_k$), then taking the difference between siblings in all variables and estimating this differenced model would yield unbiased coefficient estimates. Such an approach is possible using the NLSY data since sampling is based on family units. Unfortunately, our attempts to apply this approach were hindered by the relatively small number of sibling pairs that are observed in the sample (less than 500). Parameter estimates obtained from these sibling pairs are erratic and very imprecisely estimated and, therefore, are not reported here.

A final problem that may exist is that curriculum choice may be endogenous to many of the outcome measures considered here. A student who aspires to be a doctor, a high-paying

occupation, will likely understand the need to take more math and science classes in high school to fulfill his/her goals. In this case, the causality is reversed from outcome to high school curriculum. Estimation results will be biased towards showing a strong positive effect of math and science classes on outcomes. Again, an instrumental variable procedure could correct for this potential form of bias, but the lack of appropriate instruments prevents us from taking this approach.

This section has indicated the econometric methods employed in this analysis and has spelled out an assortment of problems which may potentially bias the results. In light of these empirical problems, the quantitative findings reported below should be interpreted with caution. Nevertheless, this paper provides important contributions. First, it catalogs many of the potential empirical pitfalls confronting the researcher. Second, it explores a variety of procedures that could possibly overcome these limitations. Third, it presents empirical findings upon which future work can build.

3. DESCRIPTION OF THE DATA

This section of the paper will provide an overview of the two data sets employed in the paper. Besides the general characteristics of the data, a discussion of the curriculum variables and test score measures is presented here. Additional details regarding the creation of the dependent variables used in this analysis are provided in the data appendix.

We use two longitudinal data sets to estimate the models presented above: the National Longitudinal Survey of Youth (NLSY) and the 1980 cohort of High School and Beyond (HSB). The NLSY first interviewed 12,686 men and women between the ages of 14 and 21 in 1979. At the time this project began, data from subsequent interviews were available through 1990 for respondents of this survey. By this point respondents are 25-32 and have largely entered the labor force. The HSB data collected information on over 10,000 seniors in high school in 1980

and reinterviewed them in 1986. While a large proportion of respondents in this sample have entered the work force they are still relatively young and measures of labor market outcomes may contain a larger transitory component.

These data have similar characteristics which allow us to address the questions and estimate the models presented above. Each data set contains a wealth of information on the labor market history of the respondents, including data on their wages and occupations. Information has also been collected on the respondents' educational experiences after completing high school, including the major field of study chosen for those who went on to college. An extensive array of personal information on the individual and on his/her family is also available. Both data sets also include sampling weights to counteract the oversampling of minorities and, in the NLSY, poor whites.

The most important characteristic of these data for the purposes of the analysis conducted here is that useable high school transcript data is available for all HSB and almost 9,000 NLSY respondents, respectively. Since the courses each respondent took come from their high school transcript and are not self-reported, these data should be quite reliable. The transcript data are not perfect, however. The HSB data has been standardized so that each course listed is the equivalent of a year-long course, but coding of the number of classes taken in a particular subject is not perfectly continuous. The codes 0-7 represent the number of half-year courses in a subject (i.e. a value of 6 represents 3 year-long courses) and a code of 8 represents four or more year-long courses. We assume that the number of students taking more than the equivalent of four years of courses in a particular subject to be small and ignore the discontinuity in this variable.

Curriculum data from the NLSY have a different problem; information on course length is incomplete so it is difficult to compare the number of courses taken across students. For example, algebra may be recorded as two half-year courses for one student and one full-year

course for another. To get around this problem, we assume that all courses in which a student enrolls are the same length within his/her own record. We then compute the percentage of classes taken in math and science for a student which can be compared across students.

Both data sets contain information on a student's aptitude/achievement in math and science. The Armed Services Vocational Aptitude Battery (ASVAB) was administered to all respondents of the NLSY (Bishop 1992, provides a detailed discussion of the ASVAB). In our analysis we use both the Armed Forces Qualifying Test (AFQT) score, which is a weighted average of four component scores from ASVAB, and scores on seven of the sections individually that relate to academic (rather than vocational) ability. Respondents of the HSB were administered an alternative battery of tests, including sections on vocabulary, mathematics, and reading. We consider each of these scores separately along with a composite score indicating the quartile of the respondent's overall score.

Finally, some restrictions were made to the data sets to arrive at the final samples used in estimation. In the NLSY, we first restricted the sample to the roughly 7,000 respondents who were surveyed in 1990 and graduated from high school (because curriculum information is difficult to interpret for high school dropouts). The few high school seniors surveyed in the HSB that did not graduate were also dropped from the sample. We then restricted the sample to workers who were employed full-time for the full year in 1990 in the NLSY (about 5,000 respondents) and 1986 in HSB (about 7,000 respondents). Our final sample sizes of 3,920 workers in the NLSY and 5,493 in the HSB represent those remaining in the sample who reported earnings. Sample sizes used in the regression analysis are somewhat smaller because of missing observations on different explanatory variables.

4. DESCRIPTIVE STATISTICS

Before presenting the results of our estimation, we provide a descriptive analysis of the data. Columns 1 and 2 of Tables 1A and 1B present means of the variables used here for all men and women separately in each of the two data sets. In the NLSY (Table 1A), we find the common result that a significant wage gap exists between men and women; women only make 74% of what men make in this sample. Education is probably not a good explanation for this wage gap since women actually have completed slightly more years of schooling than men. There is a small difference in the curriculum and test scores, however. Men take about two percent more math and science classes than women do and appear to perform better on the math and science related components of the ASVAB.

Similar results are found in the HSB data (Table 1B). A significant wage differential between men and women is apparent (the ratio of women's to men's earnings is 82%), although it is smaller than that observed in the NLSY data because the HSB respondents are younger. As in the NLSY data, men take about one-half of a year more of math and science than women do and they also perform better on the math component of the achievement tests. There is no difference in the reading and vocabulary component between men and women.

To provide a baseline estimate of the effect of taking additional math and science classes on wages, we first present simple regressions of log weekly wages on the percentage/number of math and science classes taken by gender. Results from both data sources indicate that wages rise with additional training in math and science when no other explanatory variables are included (see Table 2). In the NLSY data, assuming that an additional half-year course would represent a 2% increase (i.e. assuming the student took 25 classes in high school), an additional half-year of science would increase both men's and women's wages by about 2%. An additional half year of math would increase men's wages by the same 2%, but women's wages by about 3.5%. Evidence from the HSB data set provides somewhat smaller, but still positive returns for both men and women.

The higher wages associated with additional courses in math and science do not necessarily imply causality, however. More technical training in high school may be correlated with other characteristics of workers which lead to higher wages. To get a sense of what these factors might be, columns 3-6 of Tables 1A and 1B reports the mean values of worker characteristics separately for those men and women who have taken an above- and below-average number/fraction of classes in math and science. There are clear differences between the two groups of workers among both men and women. Above average workers come from better-educated families, score better on standardized exams, and are more likely to graduate from college. Since these other factors may be associated with higher earnings, we need to control for them in estimating the returns to additional training in math and science.

5. EFFECT OF CURRICULUM ON WAGES

Tables 3A and 3B present the estimation results from equations (1) and (2). These models separate workers by gender, and then by gender and educational attainment, and indicate the effect that additional math and science courses have on wages controlling for other personal and family background characteristics.

Our findings are roughly consistent across data sets. In both data sets and across different specifications, additional courses in math appear to increase wages for women who have graduated from college (F-tests indicate that we can reject the null hypothesis that the coefficients are equal across educational attainment levels and between men and women). Specific point estimates depend upon the treatment of test scores in these models. When test scores are omitted, an additional half-year math course (again, equal to a 2% increase in the NLSY assuming students take 25 classes in total) is estimated to increase wages by 4.5% and 5.6% in the NLSY and HSB, respectively. In models that include the full vector of test score measures, female college graduates receive 2.9% and 5.4% higher wages in the NLSY and HSB,

respectively, when they take an extra half-year course in math. On the other hand, additional courses in science do not provide a statistically significant increase in wages for any group of workers in either data set. In both data sets coefficient estimates for samples of all men and all women (i.e. not broken down by educational attainment) are close to the weighted averages of the subsample estimates.

Some discrepancies in the results between the two data sets, however, are observed. The HSB sample also yields statistically significant returns to math classes for both men with high school degrees only and to men and women who have completed some college when test scores are not controlled for. None of these groups receive a significant return to math in the NLSY data. Parameter estimates are robust to the inclusion of test scores with the exception of those obtained for men who attended some college.

The availability of high school identifiers in the HSB data allows us to estimate two additional models. First, we compute the mean number of math and science classes taken by students at a respondent's high school and use these as instruments, as detailed above. Results of this analysis are presented in columns 4 and 8 of Table 3B. The specifications reported here include the full vector of test scores, but omitting test scores yield similar results. Parameter estimates are not statistically significantly different from comparable OLS models. This finding is of little substance, however, since the IV estimates are quite imprecisely estimated with standard errors four to seven times larger than in the OLS models.

The coefficient estimates reported in Tables 3A and 3B can be used to simulate the effect of differences in the number of high school math and science classes taken between boys and girls on the wage gap between men and women. Given the estimated returns women receive from additional math and science courses in both data sets, if girls took the same amount of math and science in high school as boys, the wage gap would be reduced by no more than about one

percentage point. This result should not be surprising given the relatively small observed differences in curriculum and returns to math and science.

6. EFFECTS OF CURRICULUM ON OTHER OUTCOMES

Returns to additional technical training in high school may result indirectly from the effect of this training on educational and occupational outcomes. This section will explore these effects. For those dependent variables that are discrete, Probit models of a form analogous to equations (1) and (2) are estimated.

Tables 4A and 4B present the results regarding occupational attainment from the NLSY and HSB, respectively, in models that include test scores as explanatory variables. The dependent variables in columns 1-6 represent indices obtained from the Dictionary of Occupational Titles (DOT) which are intended to proxy the technical nature of an individual's job and are described in detail in the data appendix. Briefly, these measures include an index of the mathematics knowledge required on a job (GED Math), an index of the level of reasoning required on a job (GED Reasoning), and an index of the length of time required for an individual to learn a job (Specific Vocational Preparation; SVP). Since these technical job measures are based on indices, coefficient estimates obtained from estimating these models only provide information on the direction, not the size, of the effect of math and science courses on the technical component of an individual's job.

Estimates obtained between the two data sets are somewhat different. In the NLSY (Table 4A), women who have taken more math classes enter jobs that are statistically significantly (at least at the 10% level) more technical using each of the DOT indices. Results by educational attainment indicate that women who graduate from college and take more math are significantly more likely to enter jobs with a higher GED math index. In addition, more math classes increase the length of training time required (SVP) for jobs entered by female high school graduates. Additional math classes do not significantly affect the technical nature of the

job for men and the number of science classes is not significantly positively related to any of these DOT measures for any group in the NLSY.

Estimates from the HSB data (Table 4B) show much broader effects of curriculum on the technical nature of one's jobs. For all men and women, additional math and science classes are significantly positively related to each DOT measure. When men and women are disaggregated by educational attainment, estimates of the effects of math and science on technical jobs are mostly positively related to each DOT measure, but these effects are rarely significantly different from zero.

Tables 4A and 4B also examine the likelihood that an individual enters a job traditional for his/her sex. Since male-dominated jobs tend to require more technical skills and pay more than female-dominated jobs, if female college graduates who took more math and science were less likely to enter traditional occupations, this could explain part of their higher wages. Our findings, reported in columns 7 and 8, suggest that more math classes do indeed reduce this probability for college-educated women in the HSB data. An additional half year of math reduces the probability of entering a traditional job by almost five percentage points in these data. Male college graduates in the NLSY data set who have taken more math classes in high school appear to be more likely to enter traditionally male-dominated occupations. The traditional nature of one's job appears to be unaffected by additional math training for men and women with less education and unaffected by additional science classes for all workers.

Tables 5A and 5B examine the effect of technical curriculum on educational outcomes. Columns (1)-(4) consider the effect on the probability of attending college and of graduating from college for those who attend. Again, results from the NLSY and HSB are somewhat different. In the NLSY, men who take more math or science classes are more likely to attend college. These men, however, are not significantly more likely to graduate from college once enrolled. Women who take more math and science are not significantly more likely to either

attend college or graduate from college. On the other hand, women in the HSB that take more math are estimated to be more likely to attend college and graduate once enrolled. No such effect is observed for women who take more science classes.

Columns (5)-(8) of Tables 5A and 5B examine the choice of college major for those who graduate from college, considering whether it is technical in nature and whether it is traditional for the respondent's gender. Both of our data sets provide roughly consistent results in this area. We find that additional math classes increase the probability that women who graduate from college, major in technical fields and in fields that are not typically dominated by women. In the NLSY data, a 2% increase in high school math classes (roughly one-half year) leads to a three percentage point increase in the probability of majoring in a technical field and almost a three percentage point reduction in the probability of choosing a traditionally female major. In the HSB data, an additional half-year course in math similarly leads to about a three percentage point increase and four percentage point decrease in the probabilities of choosing a technical or traditional major, respectively.

There is less consistent evidence that these effects occur in response to additional science courses or for men. Additional science classes for women appear to be weakly associated with both an increase in the probability of majoring in technical and traditional fields. This relationship can be largely explained by those women who are planning on becoming nurses, which requires a good deal of science and is a very female-dominated field. When we restrict our sample to women who do not eventually become nurses, estimated coefficients on science classes become noticeably smaller and uniformly statistically insignificant.

7. CONCLUSIONS

This paper has examined whether taking more math and science classes increases a worker's wages, affects the type of job they go into, or influences their educational outcomes. While the specific results differ somewhat between the two data sets employed for these purposes, there are several consistent findings. We find that additional high school math classes increase the wages of those women who eventually go on to graduate from college. Both data sets show that, overall, women who have taken more math and science tend to enter more technical jobs, although results for subsamples of women with the same level of educational attainment are somewhat weaker. Finally we find that among women who graduate from college, those who take more math in high school are more likely to major in a field which is more technical and nontraditional. Findings for men are rather inconsistent across the two data sets. In both data sets and for men and women, high school science classes appear to play no significant role in determining many of the outcomes, including wages, considered here.

These results indicate that policies designed to increase the level of training in math and science may affect some educational and labor market outcomes, but these effects are far from universal. In particular, those workers with less education, for whom advancing technology may leave at a competitive disadvantage, will apparently receive little benefit from such a policy. Moreover, even though the group who apparently stands to gain the most are women who go on to graduate from college, the overall benefit for women is quite small. Our findings indicate that equalizing the level of technical training for men and women will have a negligible effect on the wage gap. Unless the returns to the technical components of a high school curriculum change significantly in the coming years, policies designed to assist workers with less education and reduce the earnings disparity between men and women should focus elsewhere.

It is important to remember, however, that the results of this analysis should be interpreted with caution. First, there are still some econometric problems which may have

biased the estimated returns to math and science classes, although Altonji (1992) argues that the bias is more likely to be towards finding effects which are "too big." Second, this research concentrates on the amount of math and science classes taken, not the quality of those classes. It is possible that students who learn more in the math and science classes they take earn higher wages, move into more technical jobs, etc. In addition, this effect may differ for men and women. Additional research investigating these shortcomings is necessary before stronger conclusions can be drawn.

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DATA APPENDIX

Some additional data needed to be merged onto the NLSY and HSB data sets to create the dependent variables employed in this analysis. One of the dependent variables represents the likelihood of an individual obtaining a job traditional for his/her sex. We define an occupation to be traditional if the percentage of people employed in the respondent's occupation that are the same sex as the respondent is greater than 70% (results are robust to alternative cutoffs). Information on the fraction of men and women in each occupation was obtained from the 1980 Census (U.S. Bureau of the Census, 1983). There are over 400 3-digit occupations defined in the 1980 Census. Since the data sets employed use occupation codes from earlier censuses, we are forced to translate between Census occupation codes in earlier years and codes used in 1980. The conversion matrices are found in U.S. Bureau of the Census (1989). A program to translate the codes and a description of the program are available from the authors upon request.

Models of the likelihood of choosing a traditional or technical college major for those who graduate from college also require definitions of these types of majors. Technical college majors have been defined by inspection and include the following broad groups of majors: agriculture and natural resources, biological sciences, engineering, health professions, mathematics, military sciences, and physical sciences. A major is determined to be traditional in an analogous manner to an occupation: if more than 70% of the degree recipients in the respondent's major are the same sex as the respondent then the major is defined to be traditional. Data on the sex composition of degree earners in each college major are obtained from The Digest of Education Statistics (1982). College major codes in the HSB are different than those from the Digest of Education Statistics. However, straightforward conversions are possible and

detailed in National Center for Education Statistics, A Classification of Instructional Programs, 1981.

The technical job indices are obtained from Dictionary of Occupational Titles (DOT) and merged onto the NLSY and HSB. The DOT data are presented in an occupational classification system different than that used by the Census Bureau, used in both the NLSY and HSB data. A program that can be used to convert the DOT codes to the Census codes is available from the authors upon request.

The measures included in the DOT data include an index of the mathematics knowledge required on a job (GED Math), an index of the level of reasoning required on a job (GED Reasoning), and an index of the length of time required for an individual to learn a job (Specific Vocational Preparation; SVP). The first two measures indicate the types of skills which are necessary to satisfactorily perform a particular job. These skills are not specific vocational skills, but those which can generally be obtained in school and are therefore called measures of "General Educational Development" (GED). In this paper, we employ the GED math level and GED reasoning level of an individual's occupation. Each of these indices range from 1 to 6. For instance, an occupation with a GED math level equal to 1 requires the typical worker to perform relatively simple numerical calculations like adding and subtracting two digit numbers. GED math level 3 occupations require workers to use intermediate mathematical skills like basic algebra and geometry and level 6 occupations require higher level skills such as advanced calculus or more sophisticated statistical analysis. An occupation at GED reasoning level 1 requires workers to "apply commonsense understanding to carry out simple one- or two-step instructions." GED reasoning level 3 occupations require workers to "apply commonsense understanding to carry out instructions furnished in written, oral, or diagrammatic form," and level 6 occupations require workers to "apply principles of logical or scientific thinking to a wide range of intellectual and practical problems."

The third measure represents the amount of time an average worker needs to prepare him/herself to complete the tasks of a particular occupation, called Specific Vocational Preparation (SVP). The amount of training time includes time spent in school, vocational programs, apprenticeships, on-the-job training, etc. The length of training is not measured continuously, but as an index ranging from 1 to 9. SVP level 1 jobs requires "a short demonstration only," SVP level 4 jobs require 3-6 months, SVP level 6 jobs require 1-2 years, and SVP level 9 jobs require more than 10 years.

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Table 1A: Mean Characteristics of NLSY Data for all Full-Time, Full-Year Workers and Those with Above And Below Average Fraction of Math and Science Courses

			Men		Women	
	(1) All Men	(2) All Women	(3) Below Average	(4) Above Average	(5) Below Average	(6) Above Average
<u>DEPENDENT VARIABLES</u>						
Weekly Wage	550.80	406.87	476.69	587.13	374.01	451.74
GED Math Score ¹	2.857	2.995	2.617	3.071	2.842	3.201
GED Reasoning Score ¹	3.689	3.958	3.484	3.872	3.827	4.136
Specific Vocational Preparation ¹	5.700	5.679	5.402	5.965	5.453	5.985
% Traditional Occupation	70.17	42.39	70.13	69.74	47.29	35.75
% Technical College Major ²	32.46	26.41	28.79	34.77	20.52	32.64
% Traditional College Major ²	32.03	27.74	29.64	33.48	29.51	25.93
<u>CURRICULUM AND TEST SCORES</u>						
% of classes in Math	11.34	10.08	8.10	14.19	7.76	13.22
% of classes in Science	9.67	8.98	6.45	12.49	6.45	12.39
AFQT score	76.57	76.65	67.09	81.31	73.57	80.76
General Science Score	17.58	15.66	15.37	18.73	14.68	16.97
Arithmetic Reasoning Score	20.37	18.27	16.98	22.23	16.81	20.22
Word Knowledge Score	27.31	27.45	25.74	28.68	26.68	28.48
Paragraph Comprehension Score	11.30	11.92	10.58	11.93	11.54	12.43
Numerical Operations Score	35.17	38.00	33.16	36.93	37.07	39.25
Coding Speed Score	45.05	52.37	42.51	47.27	51.47	53.57
Mathematics Knowledge Score	15.24	14.84	12.56	17.58	13.05	17.21
<u>PERSONAL CHARACTERISTICS</u>						
age (1990)	28.88	28.61	28.87	28.89	28.73	28.42
% Attending Some College	21.71	26.79	21.70	21.72	26.37	27.44
% Graduating College	28.94	31.00	14.29	42.19	22.36	44.42

% Urban Residence	79.20	80.15	79.24	79.16	79.25	81.37
% Residence in South	31.01	39.27	24.38	36.88	33.23	47.45
number of children	0.87	0.73	0.98	0.76	0.81	0.62
% married	61.70	53.46	62.39	61.10	54.10	52.59
% black	9.65	12.55	9.76	9.54	12.89	12.09
% hispanic	4.59	4.46	5.32	3.94	4.98	3.75

FAMILY BACKGROUND
VARIABLES³

% Urban Residence at age 14	76.44	75.44	74.50	78.15	74.97	76.09
% South Residence at age 14	28.33	35.97	21.24	34.60	28.20	46.47
Mother's Education	12.06	11.97	11.67	12.42	11.65	12.40
Father's Education	11.97	11.92	11.66	12.23	11.60	12.36
number of siblings	3.05	3.14	3.29	2.84	3.26	2.99
% reside with both parents	87.52	86.10	87.93	87.16	86.76	85.11
% reside with mother only	9.80	11.96	10.41	9.27	11.31	12.83
% mother worked at age 14	53.42	57.06	52.62	54.13	58.99	54.45
% mother's occupation traditional	60.24	59.00	57.84	62.30	58.83	59.25
% father's occupation traditional	63.33	60.53	65.63	61.41	60.75	60.18
Sample Size ⁴	2233	1687	1057	1176	993	694

Notes:

¹GED reasoning and GED math are indices proxying the technical requirements of an occupation. Specific Vocational Preparation is the average length of training time an individual needs to perform an occupation. See the Data Appendix for a more detailed description of these measures.

²Sample restricted to college graduates.

³Means for parent's characteristics are presented for those parents present in the household and, for the labor market variables, those in the labor market. In the analysis to follow, these variables are interacted with a dummy variable indicating if the parent is present in the household and, for the workforce variables, whether the parent worked.

⁴Some variables have fewer observations because of missing data. All respondents in this sample have complete high school curriculum data.

Table 1B: Mean Characteristics of HSB Data for All Full-Time, Full-Year Workers and Those with Above And Below Average Fraction of Math and Science Courses

	Men		Women			
	(1) All Men	(2) All Women	(3) Below Average	(4) Above Average	(5) Below Average	(6) Above Average
<u>DEPENDENT VARIABLES</u>						
Weekly Wage	362.86	300.52	346.73	375.40	299.85	301.94
GED Math Score ¹	2.72	2.81	2.44	2.94	2.63	3.93
GED Reasoning Score ¹	3.54	3.77	3.30	3.74	3.62	3.01
Specific Vocational Preparation ¹	5.37	5.30	5.02	5.64	5.04	5.59
% Traditional Occupation	70.69	47.73	71.4	70.0	52.1	42.7
% Technical College Major ²	33.7	23.7	25.8	36.2	13.8	29.4
% Traditional College Major ²	23.3	30.8	15.6	25.8	33.5	29.3
<u>CURRICULUM AND TEST SCORES</u>						
# Math	5.30	4.92	3.67	6.52	3.62	6.34
# Science	4.63	4.33	2.96	5.86	3.00	5.74
Quartile of Composite Test Score	2.58	2.49	2.15	2.90	2.21	2.80
Test Score in Math	9.37	8.25	6.97	11.15	6.60	10.07
Test Score in Reading	3.75	3.77	3.02	4.30	3.35	4.23
Test Score in Vocabulary	3.91	3.90	3.10	4.52	3.37	4.49
<u>PERSONAL CHARACTERISTICS</u>						
Age	24.32	24.19	24.39	24.27	24.22	24.17
% Attending College	35.50	41.17	25.48	43.23	33.00	50.40
% Graduating College	18.67	20.30	7.16	27.49	9.94	31.87
Number of Children	0.29	0.42	0.38	0.22	.482	0.36
% Married	27.72	39.39	32.24	24.17	44.56	33.58
% Black	10.10	11.06	10.03	10.03	9.55	12.58
% Hispanic	9.09	8.79	10.39	8.05	10.38	7.06
% Other Race, Nonwhite	2.36	2.11	1.79	2.80	1.71	2.57
<u>FAMILY BACKGROUND³</u>						
% High School in Urban Area	18.53	20.60	17.23	19.39	20.71	20.48

% High School in South	30.11	30.97	29.39	30.68	28.53	33.62
% Mother's Education Less than High School	14.69	18.61	19.51	11.29	22.31	14.40
% Mother High School Graduate	46.62	42.54	51.69	42.83	45.02	39.90
% Mother College Graduate	15.41	13.37	8.84	20.18	8.96	18.19
% Father's Education Less than High School	19.74	22.29	25.72	15.36	26.26	18.00
% Father High School Graduate	28.01	27.73	33.55	24.14	30.53	24.66
% Father College Graduate	24.60	20.35	11.97	33.55	13.82	27.37
Number of Siblings	3.92	3.93	4.11	3.77	4.02	3.83
% Lived with Both Parents	77.57	74.96	75.43	79.33	75.14	74.82
% Lived with Mother Only	17.09	20.06	18.33	16.08	19.80	20.26
% Mother Worked Before Elementary School	30.71	35.21	31.54	30.21	35.54	34.92
% Mother Worked Before High School	48.45	53.37	49.06	48.05	53.43	53.29
% Mother Worked During High School	64.53	69.56	64.44	64.67	69.72	69.42
Sample Size ⁴	2,657	2,836	1089	1558	1351	1479

Notes:

¹GED reasoning and GED math are indices proxying the technical requirements of an occupation. Specific Vocational Preparation is the average length of training time an individual needs to perform an occupation. See the Data Appendix for a more detailed description of these measures.

²Sample restricted to college graduates.

³Means for parent's characteristics are presented for those parents present in the household and, for the labor market variables, those in the labor market. In the analysis to follow, these variables are interacted with a dummy variable indicating if the parent is present in the household and, for the workforce variables, whether the parent worked.

⁴Some variables have fewer observations because of missing data. All respondents in this sample have complete high school curriculum data.

Table 2: The Effect of Math and Science Courses on Wages
Controlling for No Other Factors
(standard errors in parentheses)

	NLSY			HSB	
	Men	Women		Men	Women
% Math	1.051 (0.306)	1.767 (0.413)	# Math	0.014 (0.006)	0.019 (0.006)
% Science	1.193 (0.335)	0.977 (0.383)	# Science	0.008 (0.006)	0.012 (0.006)

Table 3A: The Effect of High School Math and Science Curriculum on
Log Weekly Wages of Full Year Workers, By Gender and Educational Attainment: NLSY Data¹
(Standard Errors in Parentheses)

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
<hr/>						
	ALL WORKERS ²					
CURRICULUM VARIABLES						
% Math	0.709 (0.324)	0.498 (0.332)	0.280 (0.344)	1.075 (0.390)	0.679 (0.381)	0.485 (0.383)
% Science	0.344 (0.345)	-0.216 (0.350)	-0.055 (0.355)	0.285 (0.394)	0.021 (0.394)	0.056 (0.395)
Sample Size	1891	1822	1822	1453	1427	1427
	HIGH SCHOOL GRADUATES					
% Math	0.596 (0.441)	0.654 (0.463)	0.500 (0.466)	1.176 (0.713)	0.814 (0.686)	0.703 (0.672)
% Science	0.412 (0.479)	0.041 (0.489)	0.188 (0.507)	-0.136 (0.704)	-0.216 (0.702)	-0.059 (0.704)
Sample Size	953	911	911	617	602	602
	ATTENDED SOME COLLEGE					
% Math	0.925 (0.718)	0.583 (0.659)	0.665 (0.762)	-0.043 (0.676)	-0.280 (0.683)	-0.792 (0.695)
% Science	-0.029 (0.775)	-0.257 (0.659)	-0.070 (0.798)	1.119 (0.845)	0.867 (0.878)	0.729 (0.865)
Sample Size	432	417	417	418	410	410
	COLLEGE GRADUATES					
% Math	0.758 (0.588)	0.304 (0.625)	-0.324 (0.608)	2.258 (0.597)	1.778 (0.583)	1.431 (0.619)
% Science	0.667 (0.603)	0.327 (0.626)	-0.020 (0.648)	0.306 (0.527)	-0.103 (0.500)	-0.012 (0.490)
Sample Size	506	494	494	418	415	415
ADDITIONAL CONTROL VARIABLES						
AFQT score ³	NO	YES	NO	NO	YES	NO

Individual Test Scores ³	NO	NO	YES	NO	NO	YES
Personal Characteristics	YES	YES	YES	YES	YES	YES
Family Background Characteristics	YES	YES	YES	YES	YES	YES

¹The personal and family background characteristics that are included in each model are listed in Table 1A. All estimates are weighted by the inverse probability of being in the sample. The sample is restricted to full-time, full-year workers who have graduated from high school.

²These models include dummy variables indicating whether an individual attended college or graduated from college.

³All test scores are normalized by the respondent's age at the time the tests were administered.

Table 3B: The Effect of High School Math and Science Curriculum on
Log Weekly Wages of Full Year Workers, By Gender and Educational Attainment: HSB Data¹
(Standard Errors in Parentheses)

	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ALL WORKERS ²								
CURRICULUM VARIABLES								
# Math	0.028 (0.011)	0.030 (0.012)	0.028 (0.012)	-0.017 (0.063)	0.023 (0.008)	0.023 (0.009)	0.019 (0.009)	-0.060 (0.051)
# Science	0.009 (0.009)	0.014 (0.010)	0.013 (0.010)	-0.029 (0.058)	0.002 (0.009)	0.002 (0.010)	0.001 (0.010)	0.066 (0.046)
Sample Size	2008	1828	1801	1801	2325	2150	2108	2108
HIGH SCHOOL GRADUATES								
# Math	0.028 (0.013)	0.031 (0.014)	0.031 (0.014)	-0.071 (0.082)	0.008 (0.009)	0.004 (0.010)	0.003 (0.010)	-0.038 (0.070)
# Science	-0.002 (0.011)	0.005 (0.012)	0.005 (0.012)	-0.041 (0.078)	0.004 (0.010)	0.003 (0.010)	0.003 (0.010)	0.031 (0.067)
Sample Size	1177	1068	1054	1054	1255	1150	1131	1131
ATTENDED SOME COLLEGE								
# Math	0.066 (0.028)	0.066 (0.030)	0.051 (0.035)	0.069 (0.136)	0.046 (0.019)	0.046 (0.019)	0.043 (0.019)	0.016 (0.082)
# Science	0.001 (0.020)	0.012 (0.022)	0.005 (0.025)	0.019 (0.093)	-0.007 (0.025)	-0.006 (0.025)	-0.005 (0.025)	0.133 (0.099)
Sample Size	378	341	332	332	495	458	448	448
COLLEGE GRADUATES								
# Math	0.017 (0.022)	0.037 (0.022)	0.029 (0.023)	-0.030 (0.109)	0.056 (0.021)	0.056 (0.022)	0.054 (0.024)	-0.184 (0.115)
# Science	0.033 (0.020)	0.020 (0.019)	0.017 (0.020)	-0.087 (0.103)	0.012 (0.017)	0.013 (0.018)	0.008 (0.018)	0.030 (0.071)
Sample Size	453	419	415	415	574	541	529	543

ADDITIONAL

CONTROL
VARIABLES

Composite Test score	NO	YES	NO	NO	NO	YES	NO	NO
Individual Test Scores	NO	NO	YES	YES	NO	NO	YES	YES
Personal Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Family Background Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
ESTIMATION TECHNIQUE	OLS	OLS	OLS	2SLS ³	OLS	OLS	OLS	2SLS ³

¹The personal and family background characteristics that are included in each model are listed in Table 1A. All estimates are weighted by the inverse probability of being in the sample. The sample is restricted to full-time, full-year workers who have graduated from high school.

²These models include dummy variables indicating whether an individual attended college or graduated from college.

³Two stage least squares models instrument the number of math and science classes taken by an individual with the average number of classes taken by all students in the respondent's high school.

Table 4A: The Effect of High School Math and Science Curriculum on Occupational Outcomes, By Gender and Educational Attainment: NLSY Data¹
(Standard Errors in Parentheses, Derivatives in Brackets)

Dependent Variable:	GED Math ²		GED Reasoning ²		Specific Vocational Preparation ²		Traditional Occupation ³	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women	(7) Men	(8) Women
CURRICULUM VARIABLES								
	ALL WORKERS ⁴							
% Math	0.339 (0.660)	1.939 (0.735)	-0.073 (0.599)	1.185 (0.694)	-0.467 (1.135)	2.755 (1.241)	0.642 (0.951) [0.231]	-0.957 (1.161) [-0.378]
% Science	0.307 (0.701)	-1.058 (0.673)	0.254 (0.642)	-0.946 (0.593)	-0.326 (1.146)	-1.707 (1.109)	-0.057 (0.917) [-0.021]	-0.198 (0.107) [-0.078]
Sample Size	1802	1427	1802	1427	1802	1427	1895	1473
	HIGH SCHOOL GRADUATES							
% Math	-0.542 (0.878)	1.638 (1.176)	-0.717 (0.840)	1.533 (1.080)	-2.282 (1.688)	4.006 (2.043)	-1.553 (1.367) [-0.485]	-2.175 (1.739) [-0.842]
% Science	-0.141 (0.906)	-1.443 (1.109)	0.256 (0.905)	-1.972 (1.033)	-0.469 (1.809)	-2.956 (2.022)	-0.266 (1.343) [-0.083]	-2.240 (1.650) [0.866]
Sample Size	909	605	909	605	909	605	944	623
	ATTENDED SOME COLLEGE							
% Math	0.811 (1.369)	0.133 (1.494)	1.308 (1.190)	1.366 (1.568)	2.593 (2.104)	2.366 (2.610)	2.173 (1.812) [0.765]	2.113 (2.466) [0.841]
% Science	0.321 (1.382)	-0.097 (1.285)	-0.189 (1.160)	0.237 (1.235)	-0.730 (1.974)	0.548 (2.331)	-0.529 (1.741) [-0.186]	-1.484 (2.165) [-0.591]
Sample Size	420	415	420	415	420	415	444	425

COLLEGE GRADUATES

% Math	2.069 (1.365)	4.044 (1.190)	0.390 (1.168)	1.066 (1.568)	1.623 (1.937)	1.934 (1.723)	4.344 (1.913) [1.711]	-1.248 (2.316) [-0.490]
% Science	0.848 (1.448)	-1.469 (1.035)	0.442 (1.329)	-0.423 (0.746)	0.419 (1.917)	-1.278 (1.300)	-1.014 (1.826) [-0.399]	2.521 (1.782) [0.991]
Sample Size	473	407	473	407	473	407	507	425

¹All estimates are weighted by the inverse probability of being in the sample and each model includes the individual test scores normalized by age, personal characteristics, and family background characteristics as listed in Table 1A.

²GED reasoning and GED math are indices proxying the technical requirements of an occupation. Specific Vocational Preparation is the average length of training time an individual needs to perform an occupation. See the Data Appendix for a more detailed description of these measures.

³Dummy variable equal to unity if worker's occupation is traditional for his/her gender (defined as greater than 70% of the workers in that occupation are the same gender as the worker) and zero otherwise. The sample is restricted to full-time, full-year workers who graduated from high school.

⁴These models include dummy variables indicating whether an individual attended college or graduated from college.

Table 4B: The Effect of High School Math and Science Curriculum on Occupational Outcomes, By Gender and Educational Attainment: HSB Data (Standard Errors in Parentheses, Derivatives in Brackets)

Dependent Variable:	GED Math ²		GED Reasoning ²		Specific Vocational Preparation ²		Traditional Occupation ³	
	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women	(7) Men	(8) Women
CURRICULUM VARIABLES	ALL WORKERS ⁴							
# Math	0.063 (0.021)	0.056 (0.015)	0.056 (0.019)	0.031 (0.013)	0.075 (0.035)	0.061 (0.026)	0.026 (0.025) [0.009]	-0.069 (0.023) [-0.027]
# Science	0.056 (0.021)	0.027 (0.013)	0.043 (0.019)	0.027 (0.013)	0.071 (0.034)	0.041 (0.024)	-0.002 (0.024) [-0.001]	0.006 (0.022) [0.002]
Sample Size	2028	2593	2028	2593	3038	2593	2325	2540
HIGH SCHOOL GRADUATES								
# Math	0.049 (0.023)	0.026 (0.018)	0.046 (0.023)	0.010 (0.018)	0.054 (0.043)	0.020 (0.033)	0.030 (0.032) [0.011]	-0.052 (0.031) [-0.021]
# Science	0.025 (0.025)	0.011 (0.018)	0.022 (0.023)	0.009 (0.017)	0.032 (0.043)	0.008 (0.033)	0.013 (0.031) [0.005]	0.029 (0.030) [0.011]
Sample Size	1204	1427	1204	1427	1204	1427	1388	1384
ATTENDED SOME COLLEGE								
# Math	0.031 (0.048)	0.070 (0.027)	0.027 (0.043)	0.047 (0.025)	0.070 (0.080)	0.072 (0.048)	0.029 (0.063) [0.010]	-0.041 (0.048) [-0.016]
# Science	-0.009 (0.047)	0.034 (0.026)	0.012 (0.044)	0.038 (0.024)	0.015 (0.083)	0.067 (0.048)	-0.037 (0.058) [-0.013]	-0.025 (0.045) [-0.010]
Sample Size	367	561	367	561	367	561	418	554
COLLEGE GRADUATES								

# Math	0.066 (0.056)	0.054 (0.035)	0.033 (0.042)	-0.002 (0.029)	0.049 (0.073)	0.030 (0.062)	0.058 (0.063) [0.022]	-0.122 (0.056) [-0.047]
# Science	0.116 (0.048)	0.041 (0.029)	0.067 (0.038)	0.045 (0.024)	0.139 (0.065)	0.071 (0.051)	-0.026 (0.052) [-0.010]	-0.023 (0.047) [-0.009]
Sample Size	457	605	457	605	457	605	519	602

¹All estimates are weighted by the inverse probability of being in the sample and each model includes the individual test scores, personal characteristics, and family background characteristics as listed in Table 1A.

²GED reasoning and GED math are indices proxying the technical requirements of an occupation. Specific Vocational Preparation is the average length of training time an individual needs to perform an occupation. See the Data Appendix for a more detailed description of these measures.

³Dummy variable equal to unity if worker's occupation is traditional for his/her gender (defined as greater than 70% of the workers in that occupation are the same gender as the worker) and zero otherwise. The sample is restricted to full-time, full-year workers who graduated from high school.

⁴These models include dummy variables indicating whether an individual attended college or graduated from college.

Table 5A: The Effect of High School Math and Science Curriculum on Educational Outcomes, By Gender: NLSY Data¹
(Standard Errors in Parentheses, Derivatives in Brackets)

Dependent Variable:	Attend College ²		College Graduate ³		Technical College Major ⁴		College Major Traditional ⁵	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CURRICULUM	Men	Women	Men	Women	Men	Women	Men	Women
% Math	2.896 (1.060) [1.155]	2.227 (1.350) [0.843]	0.847 (1.536) [0.338]	1.929 (1.566) [0.769]	4.305 (2.117) [1.235]	4.503 (2.352) [1.471]	2.221 (2.134) [0.713]	-3.996 (2.237) [-1.365]
% Science	3.541 (1.022) [1.412]	1.783 (1.212) [0.675]	1.111 (1.395) [0.442]	0.122 (1.415) [0.049]	4.431 (1.850) [1.271]	1.266 (2.003) [0.416]	1.340 (1.931) [0.430]	1.910 (2.029) [0.652]
Sample Size	1902	1473	957	850	501	415	482	402

¹All estimates are weighted by the inverse probability of being in the sample and each model includes individual test scores normalized by age, personal characteristics, and family background characteristics as listed in Table 1A.

²Dummy variable equal to unity if worker attended some college.

³Dummy variable equal to unity if worker graduated from college. The sample for this model is restricted to full-time, full-year workers who have attended some college.

⁴Dummy variable equal to unity if worker majored in a technical field and equal to zero otherwise. The sample for this model is restricted to full-time, full-year workers who have graduated from college.

⁵Dummy variable equal to unity if worker's major field of study in college was traditional for his/her gender (defined as greater than 70% of students in worker's chosen college major are the same gender as the worker) and zero otherwise. The sample for this model is restricted to full-time full-year workers who have graduated from college.

Table 5B: Probit Estimates of The Effect of High School Math and Science Curriculum on Educational Outcomes, By Gender: High School and Beyond Data¹
(Standard Errors in Parentheses, Derivatives in Brackets)

Dependent Variable:	Attend College ³		College Graduate ³		Technical College Major ⁴		College Major Traditional ⁵	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CURRICULUM	Men	Women	Men	Women	Men	Women	Men	Women
# Math	0.053 (0.025) [0.020]	0.068 (0.022) [0.027]	0.073 (0.048) [0.027]	0.123 (0.036) [0.046]	0.175 (0.048) [0.052]	0.087 (0.045) [0.026]	0.146 (0.054) [0.035]	-0.099 (0.042) [-0.036]
# Science	0.043 (0.025) [0.016]	0.032 (0.021) [0.012]	0.096 (0.039) [0.036]	0.020 (0.034) [0.008]	0.044 (0.042) [0.013]	0.131 (0.041) [0.039]	0.009 (0.047) [0.002]	0.097 (0.037) [0.035]
Sample Size	2303	2928	928	1282	831	971	828	968

¹All estimates are weighted by the inverse probability of being in the sample and each model includes individual test scores, personal characteristics, and family background characteristics as listed in Table 1B.

²Dummy variable equal to unity if worker attended some college.

³Dummy variable equal to unity if worker graduated from college. The sample for this model is restricted to full-time, full-year workers who have attended some college.

⁴Dummy variable equal to unity if worker majored in a technical field and equal to zero otherwise. The sample for this model is restricted to full-time, full-year workers who have graduated from college.

⁵Dummy variable equal to unity if worker's major field of study in college was traditional for his/her gender (defined as greater than 70% of students in worker's chosen college major are the same gender as the worker) and zero otherwise. The sample for this model is restricted to full-time full-year workers who have graduated from college.