High School Curricular Differences' Effects: A Look at the NELS88

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This study was motivated by the desire to find way to increase returns to education that avoided an input-based solution often used by policymakers. Unlike previous studies that utilized course-taking behavior by the student, I analyze course-requiring behavior by the school and influence-on-the-student characteristic. Using the National Educational Longitudinal Survey of the eighth grade class of 1988, I use OLS and probit models to estimate the effects of math and science requirements along with influence variables on future incomes and job satisfaction. I find that for degree-earners, math requirements had a positive effect on income, and estimates for science effects are consistently negative across both men and women. Job satisfaction was positively affected by student influence and negatively affected by parental influence. There was no significant effect on those without a degree for any case.

I. Introduction

Investigation into investment in human capital consistently emphasizes the importance of education. It is therefore pertinent to investigate ways to improve the status of education via policy implementation. Since the Coleman Report of 1964, there has been constant concern over how to overcome the strong predictive nature of socioeconomic status in analyzing secondary educational effects on future outcomes. The Coleman Report and many subsequent studies (Hanushek 2003, 2006) also brought out how simple funding is not the solution to increasing educational effects on students' lives. This study is motivated by the need to find some alternative way of increasing the relevance of education policy and therefore the effectiveness of secondary schooling. As it stands, socioeconomic status of parents is a strong predictor of any potential child's socioeconomic status, and overcoming this relatively small intergenerational mobility is a major concern for today's policymakers.[2]

Little investigation has been made into the returns to characteristics of secondary education when compared to the body of literature on higher education. This paper is focused on the returns to changes in secondary education by using variation across different schools during the same time period. Specifically, I examine how curricular variation across schools affects

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[2] Economic Report of the President, 2009.

students after graduation. This is different from the literature focusing on compulsory schooling laws, as these studies analyze school-system-wide requirements on years of schooling.

Current literature on returns to secondary education focuses on returns to each year of class that a student actually took (see Altonji 1995, Rose and Betts 2004, and Levine and Zimmerman 1995). Altonji uses the National Longitudinal Survey of the High School Class of 1972 to analyze the return to earnings of additional courses in each of eight subject areas. He finds little to no observable benefit to the level of wages for any subject, with some evidence that math and science courses influence the growth of wages. Levine uses the National Longitudonal Survey of Youth and the High School and Beyond datasets to perform a similar analysis to that of Altonji for math and science courses, differentiated by gender. He concludes that additional math and science courses produce little benefit except for females who pursue a tertiary degree. These analyses incorporate students' decisions when they have the right to choose what classes and how many to take. This represents a problem for policy-makers, as changing these inputs requires changing the incentives of the students involved based on the results of the studies done. Even then, past studies do not agree on the existence or degree of the effects of secondary education curriculum differences on postsecondary outcomes.[3]

I choose a different approach to analyze secondary education variation. Using the National Educational Longitudinal Survey dataset from 1988-2000, I used course-taking behavior that was out of the hands of the students involved. The key policy variables of interest here are requirements of math and science courses to graduate and the decision-making power of the school over gifted selection and course-taking. This removes the self-selection bias of each student once they are in a given school and creates an exogenous change in course-taking to the

[3] Altonji (1995) finds no effect of taking additional courses in any subject, and Levine (1995) finds no effect of increasing numbers of science courses. At the same time, Levine estimates that there is a return to additional math courses for females while Rose and Betts find that higher math courses benefit all students.

student. This was a major problem for Altonji and Levine, as endogenous characteristics of students would lead to such problems as reverse causality.[4] Another benefit to this method of analysis is it presents a more readily available avenue for policy implementation, since it is the schools who are able to make decisions for the students without changing student preferences. This paper examines returns across different subgroups of the cohort, including divisions by attainment of tertiary degree and gender, as in the study by Levine.

The paper is organized as follows: Section II describes the dataset used in my empirical analysis in terms of each variable used. Section III outlines the conceptual framework that will be analyzed in this paper. Section IV presents the results of the different regression specifications used and a discussion of their significance. Section V concludes and presents ideas for future research on the topic.

II. Data

This paper takes advantage of the rich National Educational Longitudinal Survey of the Eighth Grade Class of 1988 cohort.[5] It consists of a series of five questionnaires: one at the base year (1988), when the students would have been ages 13-14, and four follow-ups, one every two years for three follow-ups, with the fourth follow-up occurring in 2000. This represents the four years of secondary education along with eight years afterward for each member of the cohort. This means that at the time of the last survey, respondents were at about the age of 26. Information was gathered by the National Center for Education Statistics from the student at

[4] Levine provides the perfect example here. A student aspiring to be a doctor, which is a high-paying profession, will realize that it would be beneficial to take more math and science courses.

[5] This data was obtained through the Interuniversity Consortium for Political and Social Research via Vanderbilt University's membership.

every step, along with interviews/questionnaires for parents, school administrators, transcript reports, and cognitive tests at some of the questioning periods.

The set of dependent variables comes from answers to the fourth follow-up survey, conducted six years after the third follow-up. Income is based off self-reported income status for the respondent's current job on an hourly, weekly, biweekly, monthly, or annual basis. This was combined with the respondent's response to how often they worked in order to create, for all members of the cohort, an income variable that estimates annual income. The job satisfaction variable was derived from three different job satisfaction questions: pay, importance/challenge of job, and job security. In each question, the respondent was asked to answer either "Satisfied" or "Dissatisfied" regarding how they felt about each category. The dependent variable derived is set equal to one if all three answers are "Satisfied" and set equal to zero otherwise. This creates more variance in the dependent variable than if just one of the job satisfaction questions was used, since a large majority of respondents answered "Satisfied" for any given question.

The first set of explanatory variables comes from questions from the first follow-up of the study. This was conducted in 1990, at the time when the cohort would have been in the tenth grade. I used answers from the questionnaires of the school administrators to ascertain the data on the following graduation requirements for their high school: years of math required and years of science required.

The second set of explanatory variables is a collection of measures of influence in the student's secondary career. They are a set of binary variables that were formed from responses to the following questions: "Who is the biggest course-taking influence for the student?" and "What is the biggest factor in entrance to the gifted program at your school?" The set of binary variables are those for student, parent, and teacher course-taking influences and test scores, teacher recommendations, and parental request for entrance factors. The first question was answered by the parents of each student, and the second by school administrators.

The BYSES (Base Year Socioeconomic Status) composite variable is a combination of socioeconomic variables that were combined to produce a numerical value between -2.97 and 2.56. It is a representation of the socioeconomic status of the student's parents at the time the survey was taken in the base year (1988). It was designed by the NCES and incorporates father's education level, mother's education level, their occupations, and family income.

Table 1 summarizes the variables of interest for this analysis. The most important aspect here is the analysis of the variance in graduation requirements. Figures 1 and 2 presents a histogram of the various frequencies for years of math and science required for the entire dataset. From this picture, we can conclude there is sufficient variation to conduct this analysis.

III. Conceptual Framework

I will now describe a conceptual framework established for this study. The dependent variables of interest are income and job satisfaction in the fourth follow-up, eight years after graduation, across different pools of the cohort. To avoid the obvious return to attending post-secondary education, I have split the cohort into those who received degrees from postsecondary educational institutions and those who did not. For consistency, I have excluded those who are not employed at the time of the last survey for the study of incomes and job satisfaction. The cohort will therefore be divided as follows: those who are employed without a postsecondary degree and those employed with a postsecondary degree.

For each of these variables, there are two major specification types. The first is a test of the secondary school's curriculum on future outcomes:

$$Y_{inc} = (\vec{\beta}_{11}\vec{X}_1) + \beta_c BYSES$$

$$\Pr(Y_{sat} = 1|\vec{X}_1, BYSES) = \Phi(\vec{\beta}_{21}\vec{X}_1 + \beta_c BYSES)$$

where the vector of explanatory variables includes years of math and science required for graduation and the BYSES composite socioeconomic status variable. In addition to using the combination of math years required and science years required, each regression is run again but with only one of the two requirements. In this way, we can avoid the problem that arises as schools make decisions about graduation requirements for math and science together. The first specification and all subsequent ones that explain future income use ordinary least squares to estimate the coefficients. Each specification that uses job satisfaction utilizes a probit model using maximum likelihood to estimate coefficients on the explanatory variables.

I postulate that there is little fear for ability bias on the part of the students in the variables used to predict future income and satisfaction, as these variables are outside the control of the students themselves. The ability bias of concern, however, is that of the parents of each student. For example, a wealthy enough family may take their child from the public school system and place him or her into a private school with more stringent graduation requirements for precisely that reason. I use the BYSES variable to control for situations like this. However, since each school imposes its curriculum requirements on all students attending, it is important to realize that the variation within schools is nonexistent for this specification. It is therefore prudent to regress the data while clustering at the school level to account for the standardization within schools.

The second specification type is that of personal influences on students during their secondary experience:

$$Y_{inc} = (\vec{\beta}_{12}\vec{X}_2) + \beta_c BYSES$$

$$\Pr\left(Y_{sat} = 1 \middle| \vec{X}_2, BYSES\right) = \Phi\left(\vec{\beta}_{32}\vec{X}_2 + \beta_c BYSES\right)$$

where the vector of explanatory variables includes dummy variables of the indications of influences on the student by their parents, counselors, teachers, and themselves. This specification also includes the composite socioeconomic variable, which will be more important here. There is reason to believe that the influence of one's parents is directly correlated with a student's ability to perform outside the influence of the school. The composite socioeconomic variable takes into account all of those traits that are key predictors of a student's ability to perform and turns it into one measurement. It will serve as the proxy variable for a student's ability as a control to extract results over only the explanatory variables' effect on future outcomes.

Each regression was considered for both males and females, degree-attaining and non-degree-attaining, and the pooled gender cohort to determine where effects were most prevalent.

IV. Results and Discussion

I divided the cohort into those members who received a degree between the third follow-up and the fourth follow-up. Furthermore, for all regressions, I conditioned on being employed full-time. These two conditions imposed important restrictions on each regression. First, we avoid the college wage premium difference by only comparing within a degree or no-degree group. Second, those who are still in school or only working part-time will not have comparable wage statistics nor will their job satisfaction be as important to them. It is for this reason that only full-time employees are considered.

4.1 Effects on Income from graduation requirements

The first set of results are those of the effects on income of the two set of regressors. Table 2 reports the results of the OLS regressions with income as the dependent variable for those members of the cohort who did not receive a degree as of the fourth follow-up. The first striking characteristic is the powerful link between familial socioeconomic status and future income. This follows natural intuition and previous empirical studies (Hill and Duncan, 1987; Solon 1992) that indicate that more affluent parents tend to lead to more affluent children. If we examine the remaining regressors, we see no statistical significance established for any coefficient. In fact, these results seem to indicate that for students who do not pursue a college degree, these factors could produce positive or negative results for their later income.[6] Similar results were obtained for both males and females.

When we turn to those members of the cohort who did go on to receive a college degree after high school who were working full-time in 2000, we see surprisingly different results. Tables 3-5 report the coefficients and standard errors for the OLS regressions on income for those that received a degree. In Table 3, we see significant estimates for coefficients on years of science required and on years of math required. It appears that an extra year of math required to graduate is associated with an extra two thousand dollars in income, while an extra year in science produces the opposite result. This is in stark contrast to conventional wisdom, that more years of science leads to better future outcomes in general. The coefficient on math requirements, however, is as expected by conventional wisdom. When the two requirements are considered separate, they become less significant but retain their signs.

The next result of interest arises in the difference between the effects on men versus women. Of the regressions with separated graduation requirements, the effect of math

[6] It is interesting to note that the coefficient on the biggest course-taking influence being the teacher is negative. This is the most statistically significant of the generally insignificant results. However, this is the one result whose coefficient is still negative one standard error away from the estimate.

requirements on women was the only significant coefficient. This fits well with Levine's results that women who seek degrees benefit from additional courses of math while men do not. However, it is interesting to note that in the regressions with both requirements, men's coefficients were both more significant and greater in magnitude.

It appears that attaining a degree makes secondary education more significant for future wages for these students. This could mean that secondary education is a better preparation for higher education than it is for real-world employment directly out of high school, where more technical skills are valued. A student who leaves high school to perform manual labor will unlikely benefit much from an additional calculus course, whereas a college-bound student could find themselves ahead in a college mathematics concentration that distinguishes themselves to potential employers. The logic here is that the academic nature of standard secondary education better prepares one for college, which in turn influences to a greater extent future income.

We must now explain why math returns would be positive while the coefficients on science requirements are consistently negative. This is in contrast to the conventional wisdom that math and science classes go hand-in-hand in the learning process. It may indicate a slight but important fundamental difference in learning math versus learning science. It is important to remember here that this represents a decision on the part of the school, not the student, to take these courses. It is therefore entirely possible that the return to actively selecting to take more science courses is positive, but imposing them against the will of the students may be to their detriment. Previous studies have produced a stronger result for math curricula in the past (Levine 1995, Rose and Betts 2004), but what they may be missing is the negative aspect of imposing more classes. This is not to suggest that schools stop requiring science, but rather that these schools' science classes are not constructed in a manner that is conducive to greater returns for everyone. It is suggestive, however, that the current mathematics curriculum does impart the quantitative skills that have been shown to be beneficial after graduation (Rivera-Batiz 1992).

4.2 Effects on Income from authoritative influences

The results in columns 4 and 5 of each table suggest that authoritative influence plays a significant role in how a student performs in the future. For the men, the strongest predictor of future earnings was the presence of school policy that put control of gifted program entrance in the hands of teachers. For women, the strongest predictors of future income were gifted selection policy based on standardized test scores and their biggest course-taking influence be the students themselves. For both the men and the women, returns to parental requests being the source for gifted program selection were negative, being more significant for the women.

From the men we can infer that teachers know best how to appropriate talent in their own classroom. This follows from the intuition that only the teacher sees how the students perform in a classroom setting and can most accurately judge each student's ability. The women's different results lead to the conclusion that girls are better at representing themselves through testing than boys. In either case, parental requests represent a powerful influence over a child but at the same time are limited in their knowledge of their own child's capacity. Once in school, the learning ability of a student is more removed from the observations of the parents. It is therefore possible that parents, in search of the best possible outcomes for their children, create worse outcomes by not aligning their ideas with their children's.[7]

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[7] Reis & McCoach (2000) describe how a major cause of underachievement is conflict between the student and the parent in their analysis of the relevant literature. Dennis O'Brien of the Gifted Resource Council stresses that parents that push too hard can cause failure in their students.

4.3 Effects on Job Satisfaction from graduation requirements

The next dependent variable of interest is the constructed job satisfaction variable. Table 6 reports the probit estimates for the job satisfaction regressions for cohort members who did not receive a degree. Similar to what we saw in the regressions for income, there seems to be little significance if no college degree was received. What is surprising, however, is the one result of statistical significance: using test scores as the selection factor for the gifted program decreases the probability that one is fully satisfied with one's job.

The probit estimates for those who did receive a degree did not reveal as much as the income regressions, but were more significant than for those with no degree. Results are reported in Tables 7-9. For males, again we see a positive relationship between required math courses and the dependent variable and a negative relationship between required science courses and the dependent variable. This is explained by previous logic about the possible difference in math and science courses.

4.4 Effects on Job Satisfaction from authoritative influences

The main results from Tables 7-9 are the estimates for the coefficients on the gifted selection variables. Across all sets of regressions, gifted selection based on parental requests was statistically significant and negatively related to job satisfaction. This further supports the argument that parents are not always aware of what is best for their children. Since the dependent variable is measure of happiness, it is logical to conclude that that which will make the student happiest is what he or she actually desires. This may not show up in the income regressions, since those with high wages may be greatly unsatisfied with their work. For example, a child's parents could discover that their child excels at math and therefore forces him or her to enroll in high-level math courses. Eventually, though it may be true that this person excels at being a statistician and earns a well above average salary, in reality they would be much happier doing something else. The fact that, in the results for males, gifted selection based on teacher recommendation produces significant positive outcomes furthers the idea that the people who are closest and can more readily observe the student's achievements are best able to judge their potential.

V. Conclusion and Direction for Future Research

These results highlight the difference between degree-seekers and nondegree-seekers as it pertains to sensitivity to changes in curricula in secondary education. Generally, those who did seek a tertiary degree responded more to inputs during their secondary careers than those who eventually did not after 8 years from graduation. In their analysis, Levine and Zimmerman (1995) finds that the only group who exhibited statistically significant effects related to secondary mathematics education is female college graduates. This fits well with the results presented here, as the math requirement for graduation was significant only for those receiving a degree, and when divided, females showed a more statistically significant response to more required math courses.

The theme revealed in these results is that schools should have clear goals in mind when designing their curricula. College preparatory schools should focus on the mandating of certain classes that return the most after schooling, namely mathematics courses. This paper comes to no strong conclusions about students that do not seek degrees, so perhaps the implication here for students that do not proceed to higher education is that they take courses on a more individualized basis, letting them take that which interests them.

The discussion here opens new doors for possible future research. First, a more in-depth study of the influence of parents versus teachers on the students would be appropriate. This would give the school the justification for insistence on their methodology of assigning children to their curriculum or reason for parents to be more involved in the educational experience. Second, there is considerable opportunity to examine returns to specific class subjects. Using a dataset from an organization like the College Board for their Advanced Placement examinations to examine curricula up to and including courses in a given field could standardize results on secondary education.

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Table 1

Real-valued Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Income	7859	33,319.41	23,328.88	10,000	500,000
Mathreq	6369	2.4564	0.6171	0	4
Scireq	6385	2.1712	0.5927	0	4
BYSES	7859	-0.0518	0.7650	-2.414	2.304

Binary Variables

	Frequency	
	0	1
jobsat	2,949	4,814
Gifted selection: scores on standardized exams	320	4,754
Gifted selection: teacher rec	498	4,576
Gifted selection: parental request	2,139	2,935
Biggest course taking influence is student	4,349	3,510
Biggest course taking influence is teacher	7,314	545
Earned tertiary degree	3,659	4200

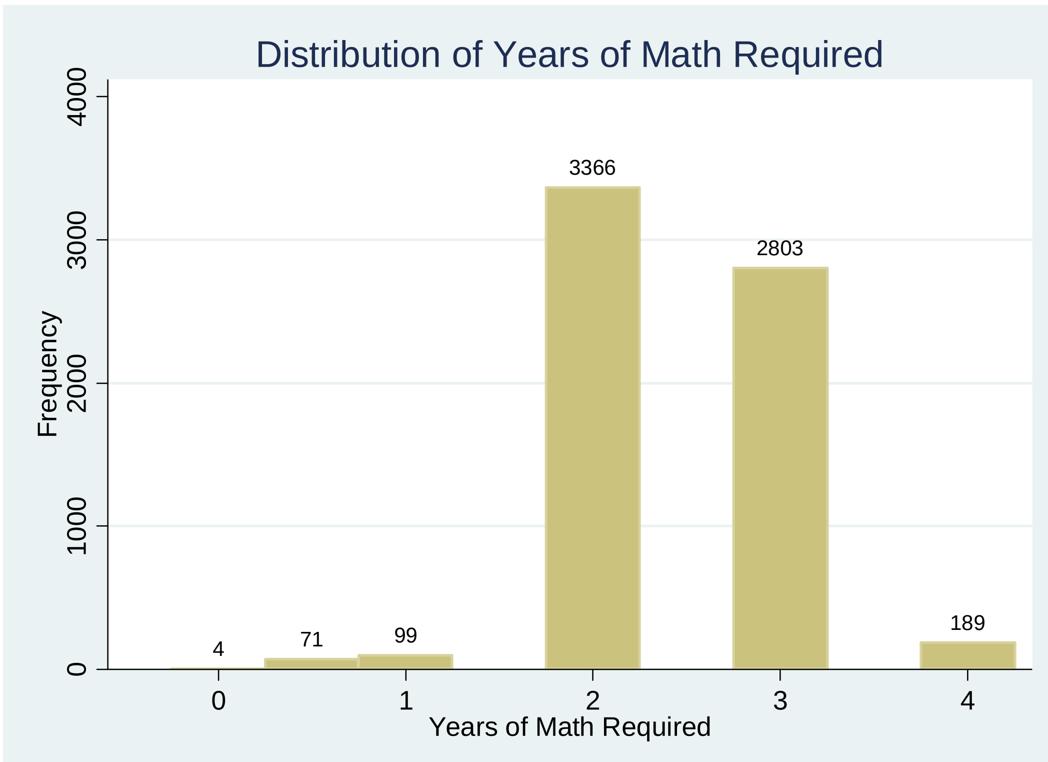
Distribution of Years of Math Required
Frequency
0
1000
2000
3000
4000
3366
2803
4
71
99
189
0
1
2
3
4
Years of Math Required

Figure 1

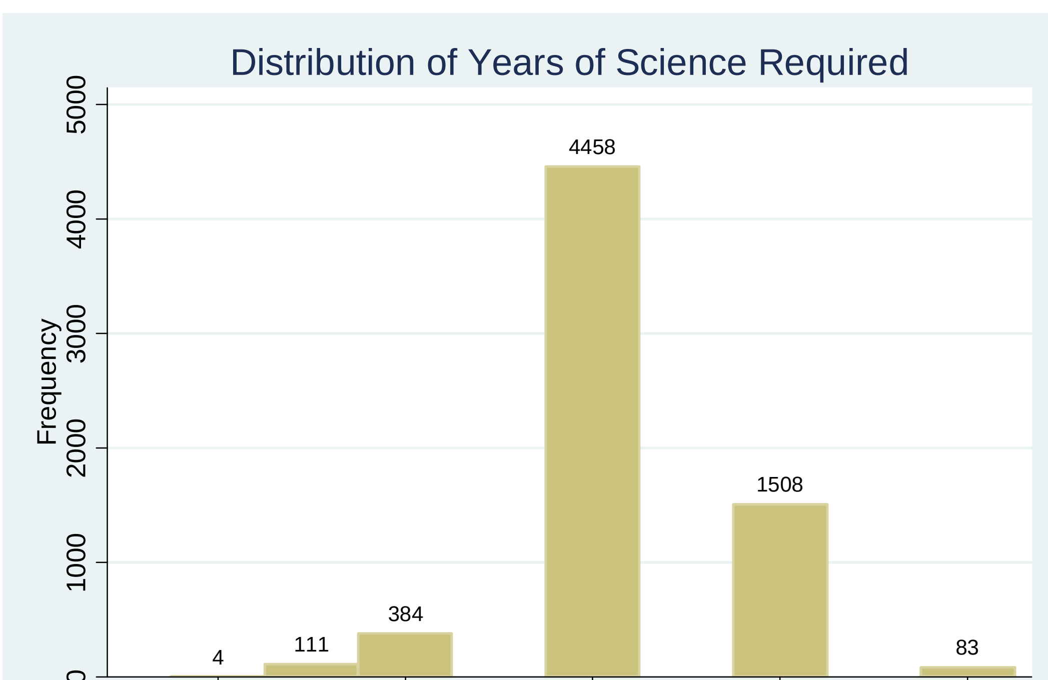
Distribution of Years of Science Required
Frequency
1000
2000
3000
4000
5000
4458
1508
4
111
384
83

Figure 2

Table 2
Income as dependent variable: No Degree

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Annual income 8 years after graduation				
socio-economic status composite	4300***	4321***	4281***	3887***	4162***
	(725.3)	(727.8)	(721.1)	(676.6)	(721.2)
gifted selection:scores on stdized exams				-1664	-1831
				(3810)	(3886)
gifted selection:teacher/counselor recom				-94.06	146.9
				(2714)	(2661)
gifted selection: parental requests				714.5	766.8
				(1124)	(1138)
Biggest course-taking influence: student				-1226	
				(1259)	
Biggest course-taking influence: teacher				-2545	
				(1595)	
Biggest course-taking influence: parent				1709	
				(1840)	
Math Required	-501.6	-114.0			
	(1142)	(891.9)			
Science Required	642.8		319.9		
	(1141)		(894.2)		
Constant	30994***	31426***	30465***	32822***	32422***
	(2310)	(2252)	(1865)	(3645)	(3501)
Observations	2981	2985	2988	2484	2484
R-squared	0.014	0.014	0.014	0.016	0.014

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust standard errors in parentheses

Table 3

Income as dependent variable: Degree

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Annual income 8 years after graduation				
socio-economic status composite	5496***	5540***	5634***	5091***	5150***
	(546.0)	(554.2)	(550.4)	(670.0)	(662.9)
gifted selection:scores on stdized exams				198.2	93.91
				(1491)	(1478)
gifted selection:teacher/counselor recom				3481***	3377***
				(1194)	(1183)
gifted selection: parental requests				-1234	-1292
				(1025)	(1023)
Biggest course-taking influence: student				2546***	
				(934.6)	
Biggest course-taking influence: teacher				5490**	
				(2598)	
Biggest course-taking influence: parent				2357**	
				(1133)	
Math Required	2386***	1091*			
	(887.8)	(592.3)			
Science Required	-2048**		-381.2		
	(1007)		(678.0)		
Constant	33871***	32575***	36110***	30252***	32521***
	(1516)	(1436)	(1502)	(1621)	(1473)
Observations	3531	3539	3552	2590	2590
R-squared	0.035	0.034	0.033	0.035	0.031

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4
Income as dependent variable: Degree
Males

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Annual income 8 years after graduation				
socio-economic status composite	6268***	6439***	6566***	6394***	6464***
	(990.9)	(1008)	(971.6)	(1198)	(1167)
gifted selection:scores on stdized exams				-4225*	-4720**
				(2474)	(2369)
gifted selection:teacher/counselor recom				6876***	6786***
				(1519)	(1504)
gifted selection: parental requests				449.4	437.9
				(1564)	(1556)
Biggest course-taking influence: student				2894*	
				(1560)	
Biggest course-taking influence: teacher				8603*	
				(4960)	
Biggest course-taking influence: parent				3554*	
				(2063)	
Math Required	2531*	487.2			
	(1386)	(982.9)			
Science Required	-3403**		-1691		
	(1627)		(1153)		
Constant	41020***	38625***	43572***	34038***	37352***
	(2743)	(2520)	(2683)	(2909)	(2474)
Observations	1603	1606	1612	1146	1146
R-squared	0.034	0.031	0.032	0.047	0.041

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

Table 5
Income as dependent variable: Degree
Females

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Annual income 8 years after graduation				
socio-economic status composite	4242***	4237***	4225***	3633***	3528***
	(510.1)	(505.1)	(505.6)	(630.4)	(638.3)
gifted selection:scores on stdized exams				3483***	3315***
				(1292)	(1262)
gifted selection:teacher/counselor recom				336.8	266.0
				(1666)	(1667)
gifted selection: parental requests				-2349*	-2438*
				(1224)	(1247)
Biggest course-taking influence: student				2251**	
				(1083)	
Biggest course-taking influence: teacher				1632	
				(1670)	
Biggest course-taking influence: parent				256.9	
				(1006)	
Math Required	1084	1035*			
	(719.7)	(612.5)			
Science Required	-70.52		718.4		
	(933.8)		(754.7)		
Constant	29000***	28964***	29917***	28014***	29500***
	(1602)	(1413)	(1482)	(1530)	(1383)
Observations	1910	1915	1922	1432	1432
R-squared	0.033	0.033	0.032	0.030	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6
Job Satisfaction as dependent variable: No Degree

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Job satisfaction (binary)		
socio-economic status composite	-0.125***	-0.123***	-0.122***	-0.0564	-0.0511
	(0.0342)	(0.0341)	(0.0341)	(0.0374)	(0.0368)
gifted selection:scores on stdized exams				-0.196*	-0.200*
				(0.112)	(0.113)
gifted selection:teacher/counselor recom				0.107	0.112
				(0.0941)	(0.0942)
gifted selection: parental requests				0.0389	0.0399
				(0.0575)	(0.0572)
Biggest course-taking influence: student				-0.0273	
				(0.0638)	
Biggest course-taking influence: teacher				-0.0720	
				(0.117)	
Biggest course-taking influence: parent				0.0308	
				(0.0791)	
Math Required	-0.0194	0.0244			
	(0.0547)	(0.0423)			
Science Required	0.0710		0.0556		
	(0.0532)		(0.0409)		
Constant	0.148	0.194*	0.134	0.341**	0.330***
	(0.110)	(0.106)	(0.0925)	(0.136)	(0.127)
Observations	2933	2937	2940	2437	2437
R-squared	.	.	.	.	.

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7
Job Satisfaction as dependent variable: Degree

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Job satisfaction (binary)				
socio-economic status composite	-0.0455	-0.0443	-0.0360	0.00390	-0.00108
	(0.0300)	(0.0300)	(0.0298)	(0.0335)	(0.0335)
gifted selection:scores on stdized exams				-0.101	-0.105
				(0.108)	(0.108)
gifted selection:teacher/counselor recom				0.230***	0.225***
				(0.0804)	(0.0804)
gifted selection: parental requests				-0.128**	-0.128**
				(0.0539)	(0.0541)
Biggest course-taking influence: student				0.0920	
				(0.0616)	
Biggest course-taking influence: teacher				0.0813	
				(0.104)	
Biggest course-taking influence: parent				-0.00264	
				(0.0714)	
Math Required	0.0880*	0.0438			
	(0.0484)	(0.0373)			
Science Required	-0.0699		-0.0105		
	(0.0491)		(0.0381)		
Constant	0.287***	0.243***	0.372***	0.241*	0.296**
	(0.0981)	(0.0931)	(0.0849)	(0.128)	(0.118)
Observations	3508	3516	3529	2570	2570
R-squared	.	.	.	.	.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust standard errors in parentheses

Table 8
Job Satisfaction as dependent variable: Degree
Males

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Job satisfaction (binary)				
socio-economic status composite	-0.0422	-0.0343	-0.0159	0.0153	0.0101
	(0.0458)	(0.0458)	(0.0452)	(0.0511)	(0.0512)
gifted selection:scores on stdized exams				-0.486**	-0.480**
				(0.202)	(0.202)
gifted selection:teacher/counselor recom				0.366***	0.362***
				(0.138)	(0.138)
gifted selection: parental requests				-0.114	-0.113
				(0.0809)	(0.0808)
Biggest course-taking influence: student				0.0416	
				(0.0958)	
Biggest course-taking influence: teacher				0.0271	
				(0.159)	
Biggest course-taking influence: parent				-0.0479	
				(0.108)	
Math Required	0.217***	0.121**			
	(0.0692)	(0.0543)			
Science Required	-0.157**		-0.0108		
	(0.0716)		(0.0557)		
Constant	0.268*	0.159	0.479***	0.615***	0.622***
	(0.143)	(0.136)	(0.124)	(0.227)	(0.218)
Observations	1592	1595	1601	1136	1136
R-squared	.	.	.	.	.

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9
Job Satisfaction as dependent variable: Degree
Females

VARIABLES	(1) jobsat	(2) jobsat	(3) jobsat	(4) jobsat	(5) jobsat
socio-economic status composite	-0.0640	-0.0653	-0.0606	-0.0114	-0.0194
	(0.0398)	(0.0397)	(0.0397)	(0.0468)	(0.0460)
gifted selection:scores on stdized exams				0.118	0.106
				(0.127)	(0.129)
gifted selection:teacher/counselor recom				0.111	0.106
				(0.111)	(0.110)
gifted selection: parental requests				-0.123*	-0.128*
				(0.0733)	(0.0737)
Biggest course-taking influence: student				0.137*	
				(0.0792)	
Biggest course-taking influence: teacher				0.0968	
				(0.145)	
Biggest course-taking influence: parent				-0.00298	
				(0.0986)	
Math Required	-0.0580	-0.0393			
	(0.0659)	(0.0482)			
Science Required	0.0282		-0.0146		
	(0.0672)		(0.0488)		
Constant	0.347***	0.363***	0.298***	0.0372	0.125
	(0.127)	(0.122)	(0.111)	(0.157)	(0.145)
Observations	1898	1903	1910	1422	1422
R-squared	.	.	.	.	.

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

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Title: High School Curricular Differences' Effects: A Look at the NELS88
Subject:
Author: Noel Whitehurst
Keywords:
Comments:
Creation Date: 4/22/2009 4:28:00 PM
Change Number: 2
Last Saved On: 4/22/2009 4:28:00 PM
Last Saved By: siegfrjj
Total Editing Time: 0 Minutes
Last Printed On: 7/10/2009 4:54:00 PM
As of Last Complete Printing
Number of Pages: 24
Number of Words: 5,444 (approx.)
Number of Characters: 31,034 (approx.)