Pergamon

Economics of Education Review, Vol. 13, No. 1, pp. 1–17, 1994
Elsevier Science Ltd. Printed in Great Britain
0727-7757/94 $6.00 + 0.00

Do School and Teacher Characteristics Matter? Evidence from *High School and Beyond*

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Abstract — This paper uses data from the *High School and Beyond* longitudinal study. We estimate the extent to which school characteristics and teacher characteristics influence the probability that public school students drop out of high school between their sophomore and senior years and, for those who do not drop out, whether these characteristics influence the extent to which students' scores on achievement tests increase during the 2-year period. The paper allows for the possibility that school and teacher characteristics are the result of both parent and teacher choices. It also statistically controls for the fact that "gain scores" are available only for students who did not drop out. School and teacher characteristics generally appear to influence gain scores more than they do drop-out probabilities. Students' gain scores are higher when teachers come from more selective institutions. The "selectivity" of a teacher's school may reflect intelligence or verbal ability, and analyses indicate that districts that pay higher salaries attract teachers from more selective institutions.

I. INTRODUCTION

NUMEROUS STUDIES have found little, if any, association between the quality of schools (usually measured by expenditure per pupil, pupil/teacher ratios, and the length of the school year or school day), or the characteristics of teachers who teach in these schools (usually measured by degree levels, experience, and teacher test scores), and student performance on standardized tests.[1] While these findings are often used by critics of public elementary and secondary education to argue against increased expenditures on schooling, this conclusion neglects a growing literature by economists that indicates that, holding education levels constant, higher school quality is associated with higher levels of earnings.[2]

Both of these literatures ignore several very fundamental issues. First, school quality and teacher characteristics may influence how long students persist in school, as well as their test scores in a given year. Hence, if one is concerned about how school quality and teacher characteristics affect labor market outcomes, one must analyze their effects on education levels, as well as their effects on test scores. Indeed, if one estimates standard "gain score" equations, without taking account of the possibility that policy variables (such as school quality) that influence gain scores may also influence drop-out probabilities, biased estimates of the effects of the policy variables on gain scores may be obtained.[3] To avoid this "selection bias" problem, one must estimate gain score models that control for the determinants of the probability that individuals in the sample are still enrolled in school.

Second, differences in school or teacher characteristics across students presumably are not randomly determined. Families choose where to live, and hence their children's schools, based on their own preferences and resource constraints.[4] Teacher characteristics depend upon factors such as the salaries teachers are offered, the number of teachers trained in an area, and the pecuniary and non-pecuniary characteristics of the community in which

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[Manuscript received 14 December 1992; revision accepted for publication 2 June 1993.]

the school is located.[5] These considerations suggest that failure to treat teacher and school characteristics as endogenous may lead to biased estimates of their affects.[6] Yet to date, virtually all studies of teacher and school affects have treated these characteristics as exogenous.[7]

Our paper seeks to take account of these issues, using data from the U.S. Department of Education's *High School and Beyond* (*HSB*) longitudinal survey. We estimate the extent to which school and teacher characteristics influence the probability that public school students drop out of high school between their sophomore and senior years and, for those who do not drop out, whether these characteristics influence the extent to which students' scores on achievement tests increase during the 2-year period. To ascertain the sensitivity of our results to the statistical methods used, the latter is done both with and without controlling for selection bias and also with and without allowing for the possibility that school and teacher characteristics are endogenously determined.

The plan of our paper is as follows. The next section sketches our analytical framework. After section III briefly discusses the *HSB* data, our econometric results are presented in section IV. The final section provides some concluding remarks and suggestions for future research.

II. ANALYTICAL FRAMEWORK

Suppose we postulate that a student's gain in an achievement test score between the sophomore and senior years in high school ($G_t = A_t - A_{t-1}$) is a linear function of vectors of characteristics of the student and his or her family (X_t), of all the students in the school and their families (Z_t), of the school (S_t), and of its teachers (T_t), as well as of the student's achievement test score in his or her sophomore year. Then

$$G_{ti} = a_o + a_1 X_{ti} + a_2 Z_{ti} + a_3 S_{ti} + a_4 T_{ti} + a_5 A_{t-1i} + \epsilon_{ti} \quad (1)$$

where ϵ_{ti} is a random error term and a_1, a_2, a_3 and a_4 are vectors of coefficients.

Least squares estimation of equation (1) will yield biased estimates if the error term, ϵ_{ti}, is correlated with any of the explanatory variables. This correlation may occur for at least two reasons. First, gain score data are available in HSB only for sophomore students who did not drop-out by, and thus have continued in school through their senior years. To the extent that any of the explanatory variables in equation (1) also influence the probability that a student drops out, these variables will also influence the probability that we observe a gain score for each individual. Thus, least squares estimation of equation (1) will yield biased estimates because the estimated coefficient of a variable will reflect both the impact of the variable on the gain score and its impact on the probability that the individual is observed to have a gain score and thus is in the sample.

Suppose we postulate that the probability that a student drops out of high school between his or her sophomore and senior years can be given by the probit equation

$$\begin{aligned} Y^*_{ti} &= b_o + b_1 X_{ti} + b_2 Z_{ti} + b_3 S_{ti} + b_4 T_{ti} + b_5 A_{t-1i} + b_6 M_{ti} + V_{ti} \\ Y_{ti} &= 1 \text{ if } Y^*_{ti} \geq 0 \\ &= 0 \text{ if } Y^*_{ti} < 0 \end{aligned} \quad (2)$$

Here Y^*_{ti} is an unobserved variable that reflects an individual's propensity to drop out of school. This is assumed to again depend on vectors of characteristics of individuals and their families, of other students and their families, of teachers and schools, and on the student's sophomore year test score (A_{t-1i}), as well as measures of labor market conditions facing the students if they drop out of school (M_{ti}), and a random error term (v_{ti}). We cannot observe Y^*_{ti}; however the student is assumed to drop out ($Y_{ti} = 1$) whenever Y^*_{ti} exceeds a critical level and to remain in school otherwise. Without loss of generality, we set this critical level equal to zero.

Heckman (1979) shows that one can obtain consistent estimates of the parameters of the gain score equation using a simple three-step procedure provided that ϵ_{ti} and v_{ti} are jointly normally distributed. First, estimate the probit equation (2) and obtain estimates of the *b*s. Note that these parameters are of interest to us in their own right because they indicate how school and teacher variables influence drop-out probabilities. Second, compute from this equation and the values of the explanatory variables for each individual, an estimate of the "inverse Mills ratio", $\hat{\lambda}$.[8] The latter can be shown to be a monotone decreasing function of the probability the individual is observed in the sample and, one can add this variable to equation

(1) and estimate this augmented equation using the method of least squares. Since inclusion of $\hat{\lambda}$ "controls" for the probability that an individual is in the sample, consistent estimates of the other parameters are obtained.

The second reason that least squares estimation of equation (1) may yield biased estimates is that the school and teacher characteristics may be correlated with the error term in (1) due to an omitted variable problem. To see this, suppose that the school characteristics in which we are interested is the student/teacher ratio, that this variable actually does *not* influence gain scores and that the omitted variable is a measure of the value that a student's parents place on education. Presumably parents who value education highly will both invest more in their children at home (thus leading to higher gain scores) and will reside in school districts with low student/teacher ratios (if they believe, erroneously in our example, that low student/teacher ratios enhance learning). Other things held constant, estimation of equation (1) by least squares would yield a negative relationship between gain scores and student/teacher ratios, even though we have assumed (for now) that the true relationship is zero.

This bias arises because of the endogeneity of families' locational decisions coupled with our inability to fully control for unobserved variables that simultaneously influence a student's gain score and his or her family's location (which in turn determines the student/teacher ratio). One way to address this problem is to use an instrumental variable estimation method to obtain instruments for variables such as the student/teacher ratio (which we believe to be endogenous) and then to estimate equation (1) using the instruments rather than the actual values of these variables.[9] We also pursue this approach below, using instruments for the various teacher and school characteristics.[10]

III. HIGH SCHOOL AND BEYOND

High School and Beyond (HSB) is a stratified national probability sample of over 1,100 secondary schools, with up to 36 sophomores and 36 seniors initially interviewed from each school in the spring of 1980.[11] Over 30,000 sophomores and 28,000 seniors participated in the base year interviews. Our focus in this paper is on the sophomores, who were given tests in mathematics, vocabulary and reading. All of the sophomores were resurveyed in 1982 and those still enrolled in school were again administered the three tests. Thus, these data provide us with information for each student on whether the student dropped out of school between the sophomore and senior year and, for those who persisted in school, the change in the average of their three test scores (gain score) over the 2-year period.[12] The individual survey data provide us with information on the characteristics of the students and their families and, since up to 72 students are present from each school, allow us to compute estimates of the value of variables that relate to all students at a school (e.g. percentage of students from low-income families).

HSB also has associated with it several auxiliary data files that enhance its value for our research. First, the base year interviews were accompanied by a survey of the participating schools. Administrators at each school provided information on enrollment, staff, programs, facilities and special programs at the school. Among the variables on which we shall focus from this school survey are measures of school quality (pupils per teacher, expenditure per pupil), measures of the racial/ethnic distributions of teachers and students at the school, and teacher characteristics (percentage of teachers with at least a master's degree, percentage of teachers with at least 10 years of teaching experience).

Second, a labor market file provides information on area-wide economic variables that might be expected to influence students' drop-out probabilities (e.g. county unemployment rates), as well as variables that may influence the supply of teacher characteristics to a given school (e.g. per capita personal income). These latter variables prove useful when we attempt to construct instruments for the teacher and school characteristics variables below.

Finally, a weakness of the HSB data is that they contain no information on teacher intelligence or verbal aptitude. Prior studies suggest that this is the single teacher characteristic that is most often seen to be related to student achievement gains.[13] However, a supplementary administrative and teacher survey was undertaken at about 320 of the HSB public high schools in 1984. Approximately 25 teachers were interviewed at each school and they provided responses to a number of questions, including the name of the institution at which they received their bachelor's degree. We matched the college each surveyed teacher attended to the ranking in Barron's (1984) of the admissions selectivity of the school in that year, with the ranking going on a 6 point scale from 1 (most selective) to 6 (nonselective). These rankings were then aggregated across teachers in a school to obtain an average selectivity ranking for the colleges that teachers at each school attended. To the extent that teachers who attended more selective undergraduate institutions have higher test scores, this measure serves as a crude proxy for average teacher "quality" at each school.

Our focus is on public schools, both because these are the schools at which educational policy proposals are often directed, and to avoid issues relating to how individual students are "sorted" between public and private institutions.[14] We also focus our attention on the three largest demographic groups of students in the sample, blacks, Hispanics, and whites.

These restrictions, along with the loss of some observations due to attrition from the sample, students changing high schools between their sophomore and senior years, and missing data, reduce the original sophomore sample of roughly 30,000 down to a sample we analyze of a little over 8,400 individuals. Analyses that make use of teacher and school characteristics variables from the school survey involve a slightly smaller sample size due to additional nonreporting of data. Finally, because the administrative and teacher survey was administered at less than half of the schools in the sample, our analyses that use the variable derived from this survey are undertaken on a further reduced sample of approximately 2,650 observations.

IV. ECONOMETRIC ESTIMATION OF DROP-OUT AND GAIN SCORE EQUATIONS

(A) Drop-out Equations

Table 1 presents selected coefficients from estimates of equation (2), the probit equation in which the probability that a high school sophomore in the base year (1980) HSB survey dropped out of school before the first follow-up (1982) survey is the dependent variable. Because of the oversampling of blacks and Hispanics that took place in HSB, we are able to report separate estimates for whites, blacks, and Hispanic students.

Estimates of six specifications are presented for each group. All specifications include a set of individual, family and area characteristics variables — the student's gender (FEMALE), dichotomous variables for the absence of either parent from the household (MOM, DAD), the parents' highest education levels (EDUCM, EDUCD), family income (INC), family size (FAMSIZE), whether the school is located in an urban area (URBAN), and the average country unemployment rate during the 1980–1982 period.[15] The latter is interacted with the socioeconomic status quartile of the student's family because previous research suggests that labor market conditions differentially influence the schooling decisions of students from high and low-income families.[16] Since our focus is on the influence of school and teacher characteristics, the coefficients of these variables are not reported in the tables that follow.[17]

All specifications also include four variables that reflect the racial and ethnic composition of students and teachers at the school. The first two are the percentages of black and Hispanic students in the school (BSTUD, HSTUD). Since the percentage of black (Hispanic) faculty in a school tends to be highly correlated with the percentage of black (Hispanic) students, to reduce collinearity the third and fourth variables are specified to be the percentage of black faculty minus the percentage of black students (BDIFF) and the percentage of Hispanic faculty minus the percentage of Hispanic students (HDIFF). Thus, the marginal effect of changing the percentage of black (Hispanic) faculty on a student's drop-out probability is estimated from the coefficient of BDIFF (HDIFF). Similarly, the marginal effect of changing the percentage of black (Hispanic) students in a school on a student's drop-out probabilities is estimated from the difference between the coefficients of BSTUD and BDIFF (HSTUD and HDIFF).

The odd-numbered columns in Table 1 exclude the base (sophomore) year achievement test composite score (BYTEST) as an explanatory variable, while the even-numbered columns include it. One would expect students who are doing well in school to be less likely to drop out, thereby providing a rationale for including the base year test score in the model. However, many of the individual, family, and school-related variables that influence the drop-out rate directly are also likely to influence the base year test score, leading to biased estimates of the former's total effect when the latter is included. So, for comparison purposes, we present estimates of both specifications of the model.

Columns (3), (4), (5) and (6) add school characteristics to the model. The percentage of students coming from the lowest SES quartile (PCTLOW), the percentage of teachers with at least a master's degree (TMA), the percentage of teachers with at least 10 years of experience at that school (TEXP), school district expenditure per pupil (PPEXP), and the number of pupils per teacher (PPT) appear in all equations. The last two columns include the mean quality rating of the undergraduate colleges that teachers in the school attended (MRATE) in the model with a lower score indicating a higher average quality.[18] Definitions of all variables appear in the notes to Table 1.

Our primary interest is in the variables that reflect the racial composition of the faculty and students at a school and in those that capture characteristics of teachers and resource levels at the school. Coefficients of these variables rarely prove to be statistically significantly different from zero, especially if one directs most attention to columns (3) and (4) which control for the racial composition variables *and* the teacher and school characteristics variables. Moreover, when a variable proves to be statistically significant, it tends to be so for only one particular race/ethnic group. However, each of these significant coefficients has a sign that one would *a priori* expect, although the magnitude of each is quite small.

For example, an increase in the percentage of Hispanic faculty is associated with a decreased drop-out rate for Hispanic students.[19] Increasing the percentages of teachers with at least a master's degree, or with 10 or more years of experience, is associated with decreased drop-out rates for black students.[20] Finally, higher per-pupil expenditure is associated with lower drop-out rates for Hispanic students.[21] While these isolated statistically significant results may simply reflect random factors, their consistent pattern does suggest that school and teacher characteristics do influence drop-out rates.[22]

(B) Gain Score Equations

Table 2 presents coefficients of the school and teacher characteristics that are obtained from estimates of various specifications of the gain score equations (equation (1) in the text). Each specification includes all of the personal, family and area characteristics variables that are postulated to influence the probability of dropping out, save for the area unemployment rate variable. Columns (1), (2) and (3) also include the racial distribution of the faculty and students variables, as well as the teacher and school characteristics variables, while columns (4), (5) and (6) include these plus the average selectivity of the undergraduate institution that the teachers at the school attended. Since sample sizes are considerably smaller in the last three columns, our primary attention will be directed at the first three columns unless we are discussing the undergraduate institutional selectivity variable. All specifications also include the base (sophomore) year achievement test score of the students.

The first column in each group of three does not control for the fact that we observe gain scores only for individuals who do not drop out of high school between their sophomore and senior years. The second and third columns in each set do, using the method described in the previous section of the text.[23] The fact that the estimated coefficient of the inverse Mills ratio, λ, is often statistically significantly different from zero suggests that selectivity bias is potentially a problem. However, it turns out that the magnitudes and statistical significance of the coefficients of the other variables do not change much across the three specifications in each set.

Our focus once again is on the racial composition, teacher, and school variables. While once again, the vast majority of these coefficients prove to be statistically insignificantly different from zero, a number of statistically significant coefficients do stand out. Moreover, unlike the magnitudes of the associations we observed in the drop-out equations, the magnitudes of some of these associations is quite large.

First, an increase in the percentage of Hispanic students is associated with an increase in the gain scores for Hispanic students. *Ceteris paribus*, an increase in the percentage of Hispanic students of 10 percentage points is associated with an increase in Hispanic students' gain scores of 0.3 points; this should be contrasted with the mean Hispanic gain score in the sample of 0.68 points.[24]

Second, *ceteris paribus*, an increase in the percentage of black faculty of 10 percentage points is associated with a 0.25 to 0.55 point increase in gain scores for white students; this should be compared to the mean white student gain score in the sample of 0.56 points. Put another way, this result suggests that black teachers, *per se*, do *not* have an adverse impact on white students' gain scores (but see below).

Table 1. Probability of dropping out of high school, sophomores (absolute value t statistic in parentheses)

	Dropout (probit)					
	(1)	(2)	(3)	(4)	(5)	(6)
White students						
HSTUD	0.016 (1.8)	0.017 (1.8)	−0.0007 (0.6)	0.004 (0.3)	−0.011 (0.4)	−0.008 (0.3)
HDIFF	0.010 (0.9)	0.013 (1.1)	−0.005 (0.3)	−0.0002 (0.0)	−0.022 (0.7)	−0.016 (0.5)
BSTUD	0.013 (4.1)	0.009 (2.7)	0.006 (1.4)	0.002 (0.4)	0.008 (1.2)	0.006 (0.9)
BDIFF	0.008 (1.5)	0.005 (1.0)	−0.0002 (0.3)	−0.006 (0.7)	0.000 (0.0)	−0.005 (0.4)
PCTLOW	—	—	0.002 (0.9)	0.001 (0.5)	0.001 (0.2)	0.000 (0.1)
TMA	—	—	0.001 (0.7)	0.0002 (0.1)	−0.001 (0.2)	−0.002 (1.0)
TEXP	—	—	−0.003 (1.7)	−0.002 (0.9)	−0.002 (0.8)	−0.000 (0.6)
PPEXP	—	—	−0.097 (1.6)	−0.091 (1.4)	−0.010 (0.1)	0.002 (0.0)
PPT	—	—	0.002 (1.1)	0.002 (1.0)	0.001 (0.6)	0.001 (0.3)
MRATE					0.061 (0.6)	0.030 (0.2)
BYTEST	—	−0.043 (10.6)	—	−0.036 (7.3)	—	−0.039 (5.6)
N(n)	5429 (1050)	5114 (922)	3665 (717)	3465 (633)	1787 (314)	1718 (287)
Log Likelihood	−1426.2	−1319.0	−1019.4	−937.29	−409.91	−389.90
Black students						
HSTUD	−0.007 (0.5)	−0.004 (0.2)	−0.030 (1.2)	−0.013 (0.5)	−0.052 (1.1)	−0.043 (0.9)
HDIFF	−0.002 (0.1)	−0.002 (0.9)	−0.018 (0.6)	0.002 (0.0)	−0.048 (0.9)	−0.032 (0.5)
BSTUD	−0.004 (1.5)	−0.008 (2.5)	−0.009 (2.1)	−0.012 (2.4)	−0.005 (0.8)	−0.010 (1.2)
BDIFF	−0.006 (1.5)	−0.008 (1.7)	−0.004 (0.7)	−0.008 (1.3)	−0.011 (1.0)	−0.018 (1.3)
PCTLOW	—	—	0.007 (1.3)	0.008 (1.4)	−0.005 (0.5)	−0.001 (0.1)
TMA	—	—	−0.007 (1.7)	−0.006 (1.3)	0.002 (0.3)	−0.001 (0.1)
TEXP	—	—	−0.007 (1.9)	−0.006 (1.5)	−0.014 (1.8)	−0.017 (2.1)

PPEXP	—	—	0.011 (0.1)	0.002 (0.0)	−0.102 (0.5)	−0.109 (0.5)
PPT	—	—	0.037 (1.7)	0.039 (1.5)	0.004 (0.1)	0.046 (0.9)
MRATE					−0.102 (0.3)	−0.027 (0.1)
BYTEST	—	−0.052 (4.4)	—	−0.053 (3.4)	—	−0.049 (2.3)
N(n)	1100 (249)	970 (188)	690 (157)	605 (119)	322 (76)	279 (58)
Log Likelihood	−316.5	−257.8	−216.5	−175.19	−108.92	−88.38
Hispanic students						
HSTUD	0.0002 (1.1)	0.002 (0.6)	−0.006 (1.9)	−0.004 (1.1)	0.001 (0.2)	0.001 (0.2)
HDIFF	−0.004 (1.2)	−0.003 (0.8)	−0.009 (2.0)	−0.009 (1.9)	−0.006 (0.8)	−0.007 (0.9)
BSTUD	0.006 (2.0)	0.003 (0.9)	−0.0004 (0.1)	−0.006 (1.1)	−0.003 (0.5)	−0.010 (1.4)
BDIFF	0.012 (2.3)	0.008 (1.3)	0.008 (1.1)	−0.001 (0.2)	−0.001 (0.1)	−0.019 (1.2)
PCTLOW	—	—	0.007 (2.1)	0.006 (1.8)	−0.001 (0.3)	−0.001 (0.2)
TMA	—	—	0.002 (0.9)	−0.002 (0.8)	−0.005 (1.2)	−0.008 (1.9)
TEXP	—	—	0.002 (0.8)	−0.004 (1.1)	0.001 (0.3)	0.002 (0.4)
PPEXP	—	—	−0.178 (1.9)	−0.180 (1.8)	−0.081 (0.5)	−0.101 (0.6)
PPT	—	—	0.005 (1.3)	0.004 (1.0)	0.002 (0.3)	0.001 (0.3)
MRATE					0.074 (0.4)	0.013 (0.1)
BYTEST	—	−0.043 (5.6)	—	−0.039 (4.2)	—	−0.042 (3.0)
N(n)	1890 (419)	1678 (349)	1287 (293)	1155 (248)	547 (124)	506 (109)
Log Likelihood	−492.6	−425.3	−360.8	−314.89	−128.58	−117.94

DROPOUT, 1 = DROPOUT, 0 = otherwise (continuing, transfer, early graduate). HSTUD, % Hispanic students, by school. HDIFF, % Hispanic teachers minus % Hispanic students, by school. BSTUD, % black students, by school. BDIFF, % black teachers minus % black students, by school. PCTLOW, % students in low SES quartile, by school. TMA, % teachers with MA or PhD by school. TEXP, % teachers at school 10 years or more, by school. PPEXP, average per pupil expenditure in the district, in 000 dollars. PPT, pupils per teachers. MRATE, mean quality of teacher undergraduate institution, by school, 1 = most selective, 6 = least selective. BYTEST, base year test score (average of non-missing reading, vocabulary and math standardized scores). *N*, number of individuals. n, number of dropouts.

Table 2. Gain score models with and without selectivity correction, sophomores (absolute value t statistic in parentheses)

	Gain					
	(1)	(2)	(3)	(4)	(5)	(6)
White students						
HSTUD	0.047 (1.5)	0.049 (1.6)	0.049 (1.6)	0.001 (0.0)	0.009 (0.2)	0.009 (0.2)
HDIFF	0.025 (0.6)	0.028 (0.7)	0.028 (0.7)	−0.029 (0.4)	−0.022 (0.3)	−0.021 (0.3)
BSTUD	0.021 (2.0)	0.022 (2.2)	0.022 (2.1)	0.033 (2.2)	0.036 (2.3)	0.036 (2.4)
BDIFF	0.025 (1.5)	0.027 (1.6)	0.027 (1.6)	0.052 (2.1)	0.053 (2.1)	0.054 (2.2)
PCTLOW	−0.088 (1.5)	−0.008 (1.6)	−0.008 (1.6)	−0.011 (1.3)	−0.010 (1.2)	−0.010 (1.2)
TMA	−0.0001 (0.0)	−0.0004 (0.1)	−0.0005 (0.1)	−0.012 (2.3)	−0.013 (2.5)	−0.013 (2.5)
TEXP	−0.0004 (0.1)	−0.0005 (0.0)	−0.000 (0.0)	0.0008 (0.2)	0.001 (0.3)	0.002 (0.3)
PPEXP	0.197 (1.5)	0.194 (1.5)	0.192 (1.5)	0.120 (0.6)	0.108 (0.6)	0.108 (0.6)
PPT	−0.004 (1.1)	−0.004 (1.0)	−0.004 (1.0)	−0.006 (1.3)	−0.005 (1.2)	−0.005 (1.2)
MRATE	—	—	—	−0.380 (1.5)	−0.416 (1.6)	−0.429 (1.6)
BYTEST	−0.173 (17.4)	−0.173 (17.5)	−0.175 (17.6)	−0.178 (12.6)	−0.182 (12.7)	−0.186 (13.0)
λ	—	−0.733 (2.8)	−0.856 (3.2)	—	−1.128 (3.4)	−1.312 (3.8)
N	3128	3128	3128	1569	1543	1543
Adj R^2	0.095	0.097	0.098	0.109	0.116	0.118
Hispanic students						
HSTUD	0.029 (2.9)	0.029 (3.0)	0.029 (2.9)	0.003 (0.1)	0.005 (0.3)	0.006 (0.3)
HDIFF	0.007 (0.5)	0.007 (0.6)	0.007 (0.5)	−0.010 (0.5)	−0.011 (0.5)	−0.011 (0.5)
BSTUD	−0.019 (1.4)	−0.018 (1.4)	−0.019 (1.4)	−0.033 (1.9)	−0.037 (2.1)	−0.038 (2.1)
BDIFF	−0.021 (1.0)	−0.021 (0.9)	−0.021 (1.0)	0.002 (0.1)	−0.006 (0.2)	−0.009 (0.2)
PCTLOW	−0.013 (1.4)	−0.012 (1.3)	−0.012 (1.3)	0.007 (0.4)	0.007 (0.4)	0.007 (0.4)
TMA	0.010 (1.4)	0.010 (1.4)	0.009 (1.3)	0.015 (1.3)	0.011 (1.0)	0.011 (0.9)
TEXP	−0.013 (1.7)	−0.014 (1.7)	−0.013 (1.7)	−0.020 (1.6)	−0.018 (1.4)	−0.017 (1.3)

	(1)		(2)		(3)		(4)		(5)		(6)	
PPEXP	0.039	(0.1)	0.041	(0.1)	0.032	(0.1)	−0.159	(0.4)	−0.236	(0.5)	0.252	(0.6)
PPT	−0.004	(0.3)	−0.003	(0.3)	−0.003	(0.3)	−0.019	(1.3)	−0.020	(1.3)	−0.020	(1.3)
MRATE	—		—		—		−0.548	(1.0)	−0.272	(0.5)	0.277	(0.5)
BYTEST	−0.190	(9.0)	−0.190	(9.0)	−0.193	(9.2)	0.194	(5.4)	−0.189	(5.2)	−0.197	(5.4)
λ	—		−0.805	(1.7)	−1.045	(2.1)	—		−1.049	(1.6)	−1.382	(2.0)
N	1055		1055		1055		487		463		463	
Adj R^2	0.088		0.090		0.091		0.064		0.069		0.072	
Black students												
HSTUD	−0.004	(0.1)	−0.002	(1.0)	−0.000	(0.0)	−0.105	(1.1)	−0.115	(1.1)	−0.113	(1.1)
HDIFF	−0.020	(0.2)	−0.018	(0.2)	−0.015	(0.2)	−0.145	(1.2)	−0.146	(1.1)	−0.142	(1.1)
BSTUD	0.0002	(0.0)	−0.0002	(0.0)	−0.0006	(0.1)	0.016	(1.3)	0.011	(0.8)	0.010	(0.8)
BDIFF	0.013	(1.1)	0.013	(1.1)	0.014	(1.1)	0.034	(1.5)	0.037	(1.5)	0.037	(1.5)
PCTLOW	−0.006	(0.5)	−0.005	(0.5)	−0.005	(0.5)	−0.011	(0.6)	−0.001	(0.1)	−0.000	(0.0)
TMA	0.015	(1.6)	0.016	(1.7)	0.016	(1.7)	0.001	(0.0)	−0.000	(0.0)	−0.000	(0.0)
TEXP	−0.013	(1.5)	−0.013	(1.5)	−0.013	(1.5)	0.012	(0.8)	0.015	(0.9)	0.014	(0.9)
PPEXP	0.545	(2.1)	0.538	(2.0)	0.542	(2.1)	0.433	(1.0)	0.755	(1.6)	0.748	(1.6)
PPT	−0.004	(0.1)	−0.005	(0.1)	−0.006	(0.1)	−0.117	(1.5)	−0.096	(1.2)	−0.095	(1.2)
MRATE	—		—		—		−1.489	(2.3)	−1.552	(2.3)	−1.532	(2.3)
BYTEST	−0.166	(6.8)	−0.168	(6.8)	−0.169	(6.9)	−0.217	(6.1)	−0.230	(6.4)	−0.232	(6.5)
λ	—		−0.717	(1.1)	−1.008	(1.5)	—		0.254	(0.3)	−0.163	(0.2)
N	549		549		549		282		254		254	
Adj R^2	0.105		0.105		0.107		0.143		0.183		0.182	

(1) — no selectivity correction; (2) — selectivity corrected, $\hat{\lambda}$ from probability of dropping out high school models, in Table 1, column (3), without BYTEST; (3) — selectivity corrected, $\hat{\lambda}$ from probability of dropping out of high school models, in Table 1, column (4), with BYTEST; (4) — no selectivity correction; (5) — selectivity corrected, $\hat{\lambda}$ from probability of dropping out of high school models, in Table 1, column (5), without BYTEST; (6) — selectivity corrected, $\hat{\lambda}$ from probability of dropping out of high school models, in Table 1, columns (6), with BYTEST.

Third, an increase in the percentage of black students at a school is associated with a zero, or slightly negative, change in white and Hispanic student gain scores, and no apparent change in black student gain scores.

Fourth, there is some evidence that teachers' degrees and experience matter. The greater the percentage of teachers with at least a master's degree, the lower white students' gain scores appear to be, but the higher black students' scores are. Having teachers with more experience, however, appears to be negatively associated with Hispanic students' gain scores.[25]

Fifth, while the number of pupils per teacher does not appear to matter, expenditure per pupil is positively associated with gain scores for both white and black students. *Ceteris paribus*, an increase in expenditure per pupil of $1,000 is associated with an increase in gain scores of 0.2 points for white students and 0.5 points for black students. At least in these data, money does matter.

Finally, gain scores are statistically significantly related to the index of average selectivity of the undergraduate colleges that teachers in the school attended. *Ceteris paribus*, an increase of one selectivity category (a decrease in MRATE of one) would increase white students' gain scores by about 0.4 points and black students' gain scores by about 1.5 points. To the extent that the selectivity ranking of an undergraduate institution is correlated with the aptitude test scores of teachers from that institution, the implication is that more able teachers, as measured by higher aptitude test scores are associated with higher gain scores.[26] Moreover, the magnitude of the relationship is larger for black students than it is for white students.

Of course, all of these results come from estimated equations that include the base year (sophomore) test score as an explanatory variable. As noted above, many variables that influence gain scores may also influence the base year test score. Hence, it is of interest to provide estimates of the determinants of base year (sophomore) test score equations, even though it is well-known that such estimates may be biased due to omitted variable problems.[27]

Table 3 presents coefficients of the school and teacher variables from our estimates of base year test score equations. As suggested above, many of the personal and family characteristics variables prove to be statistically significantly associated with the base year test scores.[28] For example, higher levels of parental education are associated with higher base year test scores for all groups, as are higher levels of family income.

Once again the racial/ethnic distribution of the faculty and students in a school appears to matter. An increase in the percentage of Hispanic students is associated with higher base year test scores for Hispanic students. In contrast, an increase in the percentage of black teachers reduces base year test scores for both white and Hispanic students, and has no effect on the base year test scores for black students. Our observation above that an increase in the percentage of black teachers is associated with higher white student gain scores is due largely to the negative association between black teachers and whiter students' base year test scores.

Higher teacher experience or expenditure per pupil are associated with higher base year scores for white pupils. However, these variables have no association with base year test scores for black or Hispanic students and no other teacher or school variable appears to be associated with the base year test scores.[29]

(C) Instrumental Variable Estimates

The estimates reported in Tables 1 and 2 treat teacher and school characteristics as exogenous. As noted in the introduction, this may lead to biased estimates of the true influences of these variables in a world in which residential location decisions of parents are based on characteristics of schools and in which teachers allocate themselves across school districts based, at least partially, on the pecuniary and nonpecuniary conditions of employment. To eliminate this potential source of bias, the instrumental variable approach described in section II can be used.

Equations were estimated to generate instruments for the faculty racial composition minus the student racial composition variables (BDIFF, HDIFF), the teacher characteristics variables (TEXP, TMA, MRATE) and the school characteristics variables (PPEXP and PPT). In each case, the actual value of these variables for a school was regressed on a set of characteristics of the families of students at the school and of the broader community (for example, percentage of students at the school from low-income families and per capita county income), the racial/ethnic composition of students at the school, and characteristics of the school (for example,

Table 3. Base year test score models, sophomores (absolute value *t* statistics)

	BYTEST (OLS) (1)	(2)	(3)
White students			
HSTUD	−0.014 (0.4)	0.051 (1.0)	0.116 (1.2)
HDIFF	0.009 (0.2)	0.049 (0.8)	0.148 (1.2)
BSTUD	−0.054 (4.2)	−0.038 (2.2)	−0.130 (1.2)
BDIFF	−0.049 (2.3)	−0.055 (1.9)	−0.074 (1.8)
PCTLOW	—	−0.054 (2.2)	−0.059 (4.3)
TMA	—	−0.008 (1.9)	0.001 (0.2)
TEXP	—	0.010 (1.0)	0.014 (1.7)
PPEXP	—	0.646 (0.8)	0.302 (1.9)
PPT	—	0.006 (1.0)	0.008 (1.0)
MRATE	—	—	−0.557 (1.3)
N	5273	3561	1753
Adj R^2	0.180	0.187	0.193
Black students			
HSTUD	−0.079 (1.2)	−0.009 (0.1)	0.100 (0.7)
HDIFF	−0.111 (1.4)	−0.065 (0.4)	−0.005 (0.2)
BSTUD	−0.017 (1.9)	−0.005 (0.4)	−0.005 (0.2)
BDIFF	−0.0002 (0.0)	−0.003 (0.1)	−0.021 (0.6)
PCTLOW	—	−0.025 (1.5)	−0.021 (0.7)
TMA	—	−0.018 (1.3)	−0.010 (0.5)
TEXP	—	−0.003 (0.2)	0.013 (0.5)
PPEXP	—	0.426 (1.1)	0.066 (0.1)
PPT	—	−0.005 (0.1)	0.056 (0.4)
MRATE	—	—	−1.559 (1.5)
N	1098	682	308
Adj R^2	0.200	0.196	0.114
Hispanic students			
HSTUD	0.015 (1.6)	0.052 (3.9)	0.037 (1.5)
HDIFF	0.014 (1.0)	0.0006 (0.0)	−0.011 (0.4)
BSTUD	−0.091 (6.6)	−0.070 (3.9)	−0.078 (3.6)
BDIFF	−0.069 (3.1)	−0.078 (2.4)	−0.132 (3.0)
PCTLOW	—	−0.085 (7.0)	−0.050 (2.9)
TMA	—	0.013 (1.3)	−0.018 (1.2)
TEXP	—	0.003 (0.2)	0.011 (0.7)
PPEXP	—	0.119 (0.3)	0.634 (1.1)
PPT	—	−0.008 (0.5)	−0.010 (0.5)
MRATE	—	—	−0.725 (1.0)
N	1787	1220	531
Adj R^2	0.189	0.220	0.225

whether minority culture is taught, and whether a desegregation order is in effect). Using the data for teachers from each school, we also first estimated, and then included in these equations, estimates of the starting teacher salary and the rates of return to experience, and to higher degrees for teachers in each school.[30]

These equations were estimated primarily to obtain instruments for the school and teacher variables and they should *not* be thought of as structural equations. Nonetheless, some interesting results were obtained that warrant at least brief reference here.

First, schools in counties with higher per capita incomes employ teachers with more experience and higher degrees, and teachers who also tend to come from more selective undergraduate institutions (lower values for MRATE). Second, an increase in the percentage of Hispanic students in a school is associated with a decrease in teacher experience and degree levels, while an increase in the percentage of black students in a school is associated with a

Table 4. Gain score models with and without instruments, sophomores coefficients of racial and school variables (absolute value t statistics)

	Gain			
	(1)	(2)	(3)	(4)
White students				
HSTUD	0.022 (1.0)	0.019 (1.6)	0.023 (2.8)	0.021 (0.7)
HDIFF	0.022 (1.0)	−0.007 (0.3)	0.007 (0.3)	−0.006 (0.2)
BSTUD	−0.003 (0.4)	−0.009 (1.0)	−0.003 (0.5)	0.019 (1.9)
BDIFF	−0.007 (0.6)	−0.026 (1.3)	0.026 (1.2)	0.020 (1.2)
TMA	—	—	—	−0.000 (0.1)
TEXP	—	—	—	−0.000 (0.1)
PPEXP	—	—	—	0.198 (1.6)
PPT	—	—	—	−0.004 (1.1)
MRATE	—	—	—	—
Observations	4674	4674	4674	3205
Adj R^2	0.091	—	—	0.093
Hispanic students				
HSTUD	0.015 (2.3)	0.002 (0.3)	0.011 (2.3)	0.027 (2.8)
HDIFF	0.007 (0.7)	−0.002 (1.5)	−0.0007 (0.0)	0.006 (0.5)
BSTUD	−0.021 (2.1)	−0.012 (1.5)	−0.006 (0.9)	−0.023 (1.8)
BDIFF	−0.025 (1.6)	−0.015 (0.6)	0.021 (0.8)	−0.026 (1.2)
TMA	—	—	—	0.010 (1.5)
TEXP	—	—	—	−0.014 (1.8)
PPEXP	—	—	—	0.179 (0.7)
PPT	—	—	—	−0.004 (0.3)
MRATE	—	—	—	—
Observations	1626	1626	1626	1117
Adj R^2	0.068	—	—	0.090
Black students				
HSTUD	−0.029 (0.7)	−0.057 (2.9)	−0.026 (1.7)	−0.006 (0.1)
HDIFF	−0.024 (0.4)	−0.105 (3.0)	−0.055 (1.3)	−0.028 (0.3)
BSTUD	0.002 (0.4)	−0.009 (1.3)	−0.009 (1.5)	0.001 (0.1)
BDIFF	0.013 (1.4)	−0.023 (1.1)	−0.048 (2.0)	0.015 (1.4)
TMA	—	—	—	0.018 (2.0)
TEXP	—	—	—	−0.010 (1.2)
PPEXP	—	—	—	0.390 (1.5)
PPT	—	—	—	0.007 (0.2)
MRATE	—	—	—	—
Observations	997	997	997	623
Adj R^2	0.062	—	—	0.080

Variables: (1) Gain model with no instruments. (2) Gain model with instruments for BDIFF and HDIFF estimated from models that excluded estimated rates of return to experience and degree. (3) Gain model with instruments for BDIFF and HDIFF estimated from models that included estimated rates of return. (4) Gain model with no instruments.

decrease in teacher experience and an increase in the pupil/teacher ratio.[31] Third, teacher salary variables matter. An increase in the estimated rate of return to holding a postgraduate degree is associated with an increase in the percentage of teachers with such degrees, while higher starting salaries are associated with an increase in the selectivity of the colleges that teachers in a school attended (a decrease in MRATE).

Table 4 contains selected coefficients from the gain score equations for the racial/ethnic distribution variables and the teacher and school characteristics variables. Coefficients from three models are presented and, in each case, the first column presents estimates obtained using the actual values of the variables, while the latter two columns present estimates obtained using the instrumental variables.[32]

For the most part, the estimates obtained using the instrumental variables method are quite similar

Table 4 — *Continued*

		Gain		
(5)	(6)	(7)	(8)	(9)
0.023 (1.3)	0.028 (2.6)	0.002 (0.0)	0.061 (2.2)	0.074 (2.0)
−0.012 (0.4)	0.006 (0.3)	−0.029 (0.4)	0.055 (1.1)	0.108 (1.8)
0.017 (0.4)	0.007 (1.0)	0.033 (2.2)	0.004 (0.2)	0.018 (0.9)
0.009 (0.3)	−0.045 (1.4)	0.052 (2.1)	−0.027 (0.6)	−0.002 (0.0)
0.015 (1.4)	−0.008 (0.6)	−0.012 (2.3)	0.019 (0.9)	−0.032 (1.7)
0.004 (0.4)	0.017 (1.3)	0.001 (0.2)	−0.004 (0.2)	−0.017 (0.8)
−0.029 (0.1)	0.586 (1.2)	0.120 (0.6)	0.290 (0.6)	0.525 (0.8)
−0.004 (1.1)	−0.003 (1.1)	−0.006 (1.3)	−0.005 (1.1)	−0.005 (1.4)
—	—	−0.320 (1.5)	0.039 (0.0)	−1.792 (2.1)
3205	3205	1569	1569	1569
—	—	0.109	—	—
0.011 (0.9)	0.022 (3.0)	0.003 (0.1)	−0.028 (0.7)	−0.024 (1.0)
−0.029 (1.4)	0.0003 (0.0)	−0.010 (0.5)	−0.086 (1.2)	−0.061 (1.7)
−0.016 (1.2)	−0.008 (0.8)	−0.033 (1.9)	−0.065 (1.6)	−0.062 (2.9)
−0.027 (0.7)	0.033 (0.7)	0.002 (0.1)	−0.089 (0.8)	−0.085 (1.2)
0.030 (1.4)	0.021 (0.8)	0.015 (1.3)	0.054 (0.7)	0.022 (0.6)
−0.003 (0.1)	−0.013 (0.5)	−0.020 (1.6)	0.048 (0.7)	0.021 (0.6)
−0.326 (0.5)	−0.885 (0.8)	−0.159 (0.4)	−0.189 (0.1)	−1.043 (0.8)
−0.003 (0.3)	0.003 (0.5)	−0.019 (1.3)	0.009 (0.4)	0.005 (0.7)
—	—	−0.548 (1.0)	2.569 (0.8)	0.092 (0.1)
1117	1117	487	487	487
—	—	0.064	—	—
−0.046 (1.2)	−0.005 (0.2)	−0.105 (1.1)	−0.069 (0.7)	0.048 (0.4)
−0.092 (1.5)	−0.006 (1.2)	−0.145 (1.2)	−0.078 (0.4)	−0.020 (0.1)
−0.016 (1.2)	−0.015 (1.5)	0.016 (1.3)	−0.034 (0.9)	−0.029 (0.8)
−0.047 (1.2)	−0.103 (1.8)	0.034 (1.5)	−0.135 (1.2)	−0.172 (1.2)
0.036 (1.0)	0.015 (0.3)	0.001 (0.0)	−0.048 (0.4)	−0.070 (0.6)
−0.005 (0.2)	−0.003 (0.1)	0.012 (0.8)	−0.027 (0.3)	−0.015 (0.2)
0.171 (0.2)	1.051 (0.6)	0.433 (1.0)	0.543 (0.2)	1.493 (0.5)
−0.004 (0.4)	−0.005 (0.5)	−0.117 (1.5)	−0.014 (0.5)	−0.015 (0.7)
—	—	−1.489 (2.3)	−3.878 (0.9)	−4.367 (1.1)
623	623	282	282	282
—	—	0.143	—	—

(5) Gain model with instruments for BDIFF, HDIFF, TEXP, TMA, PPEXP, PPT estimated from models that excluded estimated rates of return. (6) Gain model with instruments for BDIFF, HDIFF, TEXP, TMA, PPEXP, PPT estimated from models that included estimated rates of return. (7) Gain model with no instruments. (8) Gain model with instruments as in (5) and MRATE estimated from models that excluded estimated rates of return. (9) Gain model with instruments as in (6) and MRATE estimated from models that included estimated rates of return.

Absolute value t statistics for models with instruments are calculated using "corrected" standard errors. Adjusted R^2 are not reported for models with instruments. Models with instrumental variables also include a dummy for observations where instruments are unknown = 1.

to those obtained using the raw data. However, there are some exceptions. On the one hand, the effect of the selectivity of the colleges that teachers in a school attended is larger for white students when the instrumental variable approach is used (compare columns (7) and (9)). On the other hand, the proportion of teachers with advanced degrees, which was significantly positively related to the gain scores for black students (column (4)) now ceases to be statistically significant (columns (5) and (6)).

IV. CONCLUDING REMARKS

Do school and teacher characteristics matter? Our analyses of data from the 1980 and 1982 waves of the original HSB sophomore cohort provide somewhat ambiguous evidence on this question. For the most part, variables that represent the characteristics of schools and teachers, or the racial/ethnic composition of a school's teachers and students, rarely prove to be statistically significant predictors of a student's probability of dropping out of high school between the sophomore and senior years or, if the student did not drop out, of the change in the student's achievement test scores between the two years. However, some variables do influence either drop-out rates or gain scores, and the magnitudes of these responses is quite large in the gain score case.

A major innovation of our paper lies in the econometric methods we use. It represents the first attempt, to our knowledge, to both correct for possible sample selection bias and to control for the possible endogeneity of school and teacher characteristics when estimating "gain score" equations. Although in the present case the use of these methods did *not* substantially alter any of our findings, the possibility that these statistical problems may exist suggest that future "educational production function" researchers should consider using the methods we have sketched out here.

Our findings to date also suggest a number of important directions in which future research might proceed. First, our analyses of the influence of school and teacher characteristics, using the original sophomore HSB cohort, can be extended to later stages of the cohort's educational and labor market histories. In particular, the likely availability of data in late 1993 from the 1992 follow-up survey for this cohort will provide other researchers and ourselves with up to 10 years of post high school data for cohort members. This will permit estimation of how characteristics of schools and teachers influence the probability of entry into post secondary education, the number of years of post-secondary education received, the measures of early labor market success, such as wages and weeks of employment.

Second, the analyses we have undertaken to date can be extended using other data bases. For example, we have estimated the effects that the overall race/ethnic distribution of teachers and students in a school have on gain scores and drop-out probabilities for individual students from different race/ethnic groups. However, it would be desirable to try to disentangle whether the race/ethnic distribution of an individual student's immediate classmates and teachers have effects above and beyond the effects that the school-wide distributions have. The *National Educational Longitudinal Study of* 1988 (*NELS*88), which uniquely matches individual teachers and students, seems to be an ideal data set to use to address this question.[33]

To take another example, we have shown that the average "selectivity" of the undergraduate institutions that teachers in a school graduated from has an important influence both on students' gain scores and their base year test scores. To the extent that institutional selectivity is a proxy for the verbal ability, or the intelligence, of teachers in the school, we have provided indirect evidence on the importance of this teacher characteristic in the educational process. While others (for example, Ferguson, 1991), have recently directly addressed the issue of teacher verbal ability using school district level data, the only data set of which we know that contains verbal aptitude data for individual teachers, along with individual students' test scores, is the original 1965 *Equality of Opportunity Survey* (EEOS) data.[34] Reanalysis of the EEOS data, applying the methodological advances of the last 20 to 25 years to address issues raised by critics of the original Coleman Report, should enhance our understanding of the importance of teacher verbal aptitude.[35] In particular, the EEOS data is unique in its ability to provide insights about whether the verbal ability of teachers of different races is an important predictor of the gain scores of students of different races.[36]

Acknowledgements — Our research was supported by the William H. Donner Foundation and the Finance Center of the Consortium for Policy Research in Education (CPRE). CPRE is a consortium of the University of Southern California, Rutgers University, Cornell University, Harvard University, Michigan State University, and the University of Wisconsin-Madison and is funded by grant No. R1178G10039 from the US Department of Education, Office of Educational Research and Improvement. The views expressed are those of the authors and are not necessarily shared by the William H. Donner Foundation, CPRE, or the US Department of Education.

NOTES

1. For reviews of the "educational production function" literature, see Hanushek (1986) and Harbison and Hanushek (1992), Chapter 2.
2. See, for example, Welch (1966), Morgan and Sirageldin (1968), Johnson and Stafford (1973), Wachtel (1976), and Card and Krueger (1992).
3. This is the by now well-known "sample selection" bias problem. See Heckman (1979).
4. See Tiebout (1956).
5. See Ferguson (1991).
6. Evans, Oates, and Schwab (1992) make a related point in the context of estimating "pear group effects" on drop-out rates. While they treat peer group measures, such as the percentage of disadvantaged students in a school as endogenous, they do not explore the influence of teacher or school characteristics on drop-out rates.
7. Ferguson (1991) treats teacher and school characteristics as exogenous when he estimates district-level educational production functions, but then goes on to show how these characteristics vary with underlying socioeconomic and demographic variables.
8. Formally, $\hat{\lambda}$ is equal to the density function of the standard normal variable divided by one minus the cumulative distribution function of the variable, both evaluated at a value determined by the parameters of the probit and the values (for each individual) of the explanatory variables.
9. Evans, Oates and Schwab (1992) use this method to estimate peer group effects.
10. In principle, one should also use a similar approach when estimating the drop-out probit equations, but we do not pursue this in the paper.
11. See National Center for Education Statistics (1983) for a detailed description of the *HSB* data set.
12. A subsample of the sophomores were also resurveyed in 1984, 1986, and 1992. The latter data should be available in the fall of 1993 and will permit us to analyze how teacher and school characteristics influence these students' college-going behavior, education levels (10 years after high school graduation) and early career labor market success.
13. See Harbison and Hanushek (1992), Chapter 2.
14. See Chubb and Moe (1990) for an attempt to control for students selection into public and private schools.
15. Missing variables are a serious problem in HSB. To maintain our sample size at reasonable levels, dichotomous variables were also included if father's or mother's education were not reported, or if family income was not reported.
16. See Ehrenberg and Marcus (1982). While it would be desirable to include a measure of wages available by county, as well as the unemployment rate in the analyses, HSB does not include a county wage variable. The state manufacturing wage rate is included in the HSB labor market file and we included it in our preliminary analyses. However, coefficients of this variable never proved to be statistically significantly different from zero.
17. More complete tables of results, that correspond to Tables 1, 2 and 3 in this paper, are available in an earlier version of the paper that is available from the authors on request.
18. As noted above, sample sizes decline substantially when this variable is included.
19. An increase in the Hispanic faculty of 10 percentage points (e.g. from 10 to 20 per cent) decreases the probability of a Hispanic student dropping out by 0.00094 (all other variables held constant at their mean values). The mean drop-out probability for Hispanic students is 0.218 in this sample. Hence, a 10 point increase in the percentage of black faculty is associated with about a 0.4 per cent ($100 \times 0.00094/0.218$) decrease in the Hispanic student drop-out rate.
20. A 10 percentage point increase in the percentage of teachers with at least a master's degree and a similar increase in the percentage of teachers with at least 10 years of teaching experience decrease the probability of black students dropping out of school by 0.00144 and 0.00166, respectively, all other variables held constant at their mean values. Given the black student drop-out rate in the sample of 0.250, these effects would be equivalent respectively to 0.6 and 0.7 per cent reductions in the drop-out rate.
21. An increase of 10 per cent in expenditure per pupil is associated (at the mean of all other variables) with a decrease in the Hispanic student drop-out rate of 0.00256, which is equivalent to a 1.2 per cent reduction in the drop-out rate.
22. The problem here is that the number of racial composition, teacher characteristics, and school variable coefficients that prove to be statistically significant is small relative to the total number of these coefficients that we estimate. If all coefficients were in fact truly zero, random factors would cause 5 of them to appear to be statistically significantly different from zero at the 0.05 level of significance. However, if *all* of the significant coefficients are of the signs one *a priori* expects, the likelihood that one is observing systematic relationships increases.

23. These methods make use of the probit equations presented in Table 1. See the notes to Table 2 for the specifications we use to control for selectivity.
24. Recall that the marginal impact of changing the percentage of Hispanic students is given by the coefficient of HSTUD minus the coefficient of HDIFF. Since the latter is never statistically significantly different from zero here, this simulation uses only the former.
25. The Hispanic population has grown rapidly in the U.S. since 1970. Teachers with more than 10 years of experience in 1980 very likely had little experience with Hispanic students during the teacher's "formative" years and thus may have formed stereotypes that hindered their effectiveness in teaching Hispanic students.
26. Ferguson (1991) provides similar evidence.
27. See Hanushek (1986).
28. Again, these results are available from the authors on request.
29. The coefficient of MRATE is negative (implying higher base year test scores are associated with teachers having attended more selective undergraduate institutions) for all three groups. However, whilt its t statistic is always greater than 1.0, its coefficient is not statistically significantly different from zero for any of the three groups.
30. Appendix Table A1 in the longer version of the paper, which is available from the authors, enumerates the variables included in these analyses, indicates how the starting salaries and rates of return were estimated, and presents the estimated equations.
31. Whether these student racial/ethnic distribution results are due to discrimination, differences in preferences for education, and/or teacher supply behavior, cannot be determined from the data.
32. See the notes to Table 4 for details.
33. *NELS88* surveyed students and teachers initially when the former were in the 8th grade. A follow-up survey undertaken in 1990 when the students were in the 10th grade is now available. The 1992 follow-up, conducted when the students were in the 12th grade, will likely be available in 1994. See National Center for Education Statistics (1990) for details of *NELS88*.
34. See Mosteller and Moynihan (1972) and Coleman *et al.* (1966) for discussions and analyses of the *EEOS* data.
35. Among the criticisms of the Coleman Report was that it analyzed only data on the test scores of students at a single point in time. Test scores may vary across students at a point in time because of unobserved characteristics of the students, their families, and their school district. To the extent that these unobserved characteristics are correlated with included variables, biased estimates of the coefficients of the observable variables will result (see Hanushek, 1986).

    As a consequence, the post Coleman Report literature has emphasized using "gain scores" as the outcome to be explained; this permits one to "difference out" the effects of the omitted variables. Since tests were administered to students in several different grades in the *EEOS*, it is possible to compute "synthetic gain scores" (e.g., average sixth grade score in a school minus the average third grade score) and use this as the outcome to be explained. Surprisingly, to our knowledge, until Ehrenberg and Brewer (1993), no one reanalyzed the *EEOS* data in this way.
36. Our own preliminary findings are reported in Ehrenberg and Brewer (1993).

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