The Determinants of Undergraduate Grade Point Average: The Relative Importance of Family Background, High School Resources, and Peer Group Effects

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ABSTRACT

The paper analyzes the Grade Point Average (GPA) of more than 5,000 undergraduates at the University of California, San Diego. Personal background strongly affects GPA. Graduates of different high schools obtain significantly different GPAs, even after controlling for personal background. These school effects in part reflect the incidence of poverty and the level of education among adults in the school neighborhood. Teachers' experience in the student's high school bears a positive and significant link to the student's university GPA, but the effect is small. No such positive link with GPA emerged for the teacher-pupil ratio or teachers' level of education.

I. Introduction

What explains variation in college students' performance? In the typical university, measures of student success such as Grade Point Average (GPA) show substantial variation. Of course, to some extent this diversity reflects differences in the degree of difficulty among different programs of study within the univer-

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sity. But disparities in GPA surely also reflect variations in the level of preparation of freshmen undergraduates.

It is useful to study the determinants of college GPA because GPA reflects human capital acquisition at a time when young adults are close to permanent entry into the labor force. Many studies have found a positive and significant link between college GPA and subsequent earnings. Most recently, Loury, and Garman (1995) find that weekly earnings of white males in the National Longitudinal Study of the High School Class of 1972 are predicted to rise by 10.0 percent with a one-point increase in college GPA. For black males, the corresponding estimate is a 28.7 percent increase in earnings, although the point estimate is significant at only the 5.3 percent level. These results are impressive because the earnings equation controls for college selectivity, the person's own score on the Scholastic Aptitude Test (SAT) and family background. Other studies that have found a positive and significant relation between college GPA and earnings include Jones and Jackson (1990), Filer (1983), and Wise (1975). Similarly, Grogger and Eide (1995) report a positive relation between high school grades and earnings.

This paper seeks to determine the factors underlying variations in student performance, measured by GPA, at a major public university. It considers four sets of explanatory factors:

1. the degree program in which students are enrolled at university,
2. the student's family background (such as family income and race),
3. the resources of the high school that the student attended prior to enrolling in university (measured by variables such as the traits of teachers and the teacher-pupil ratio),[1] and
4. the demographic environment in which the student attended high school (for example, characteristics of the student body and levels of education or income in the community).

This study should prove of interest to two distinct academic communities. First, the study provides a relatively new and novel method for determining the extent to which high schools vary in effectiveness. Ever since the Coleman Report (1966) was released, the academic community has invested a great deal of effort in an attempt to explain why public schools differ in quality. The vast majority of prior research in this field has measured student success in terms of the test scores of students while in grade school. Ideally, we would like to follow students after high school to test whether school spending translates into better outcomes for students once they begin their adult lives. The present paper follows students several years past their high school graduation in an effort to measure the relative effectiveness of high school resources in terms of how students fare once they arrive at university.

The second policy community to which this research is directed are college admin-

1. We were unable to obtain measures of school inputs at the level of the student's high school classroom. This prevents us from testing for nonlinearities in the relation between school inputs and student outcomes in university. But on the other hand, using school-level averages overcomes the potential endogeneity bias that would result from using data at the classroom level if schools change the mix of inputs that go into each classroom.

istrators, who each year sift through tens of thousands of applications for undergraduate admissions in an attempt to identify the best candidates. At many universities, high school GPA and scores on the Scholastic Aptitude Test (SAT) play a key role in these admissions decisions. Our research will first test whether high school GPA and SAT scores provide reliable predictors of GPA. Second, it will test whether other characteristics of the students, or of the high schools from which they graduated, can improve on simple forecasts of students' success in university that are based on high school grade and test scores alone.

The next section reviews the literature on school quality in detail, and demonstrates the new contributions to the literature made by the present paper. Section III describes the data. Section IV details the results of reduced form models that analyze university GPA in terms of high school traits and family background. Section V examines the extent to which these traits help to forecast university success in models which already condition on SAT scores and high school grades.

II. Literature Review

There now exists a large literature on the role that the characteristics of public schools play in determining students' test scores. Reviews by Hanushek (1986, 1989, 1991, 1996) find that the vast majority of papers in this area have found surprisingly little correlation between school traits such as class size and students' test scores.

But researchers have also examined the determinants of school quality in two other ways: they have searched for a link between school traits and both educational attainment and earnings after graduation. The literature on school quality and earnings has found mixed results. See for instance Card and Krueger (1992), Betts (1995, 1996a), Grogger (1996), and the review by Betts (1996b). Of particular relevance to the present paper is a finding by Heckman, Layne-Farrar, and Todd (1996). In replicating earlier work by Card and Krueger (1992), Heckman and his coauthors find evidence that school resources are positively related to the earnings of only those workers who obtain college degrees. This makes it important to verify whether high school resources influence academic success of those who attend college. Such is the goal of the present paper.

The impact of public school resources on educational attainment has received relatively little attention. The review by Betts (1996b) finds only 14 published studies of the link between school resources and educational attainment. Most of these studies have examined only years of education as the outcome variable. Arguably, it is more interesting to examine whether students receive college degrees, rather than the student's total years of schooling, because it is well known that earnings depend strongly on degrees obtained. (This "sheepskin effect," whereby the economic returns to years of schooling makes nonlinear jumps for those who have obtained high school or college diplomas, has been documented by Hungerford and Solon 1987, among others.)

Similarly, it is interesting to know how high school characteristics influence the Grade Point Average (GPA) of students once they arrive at university. To the best of our knowledge, only one published work has ever examined this question. This paper, by Raymond (1968), modeled average freshman GPA at West Virginia University as a function of school inputs and demographic traits. The unit of observation for all variables was the county. Raymond finds that spending per pupil, the pupil-teacher ratio, and school library resources bear no relation to freshman GPA, although he did find in some specifications that teachers' salaries were positively linked to GPA. He also reports that the demographic traits of the county were significantly linked to freshman GPA. It is important to note that this study does not use GPA at the level of the individual student. Furthermore, it does not control for the individual's family background, nor does it measure school resources at the actual school attended.

The goal of the project is to model the university GPA of students at the University of California, San Diego (UCSD), as a function of characteristics of the students at the time they enter university. This work has both administrative and academic uses. To academic researchers it will provide some of the first evidence on the role which individual high schools play in promoting student success in college. Furthermore, it will be of help to universities in trying to determine what factors should be used in attempts to predict the likelihood of success should a student be admitted.

We use a rich longitudinal database on undergraduate students enrolled at UCSD to search for a link between high school characteristics and GPA. The dataset contains detailed information about the actual high school attended, family background and demographic information on the school and school district that the student last attended.

Recent work by Morell (1993a,b) establishes that existing databases maintained at UCSD can be successfully used for research purposes. Her earlier work shows strongly significant positive links between high school GPA and test scores and success of undergraduates at UCSD, where success is measured in terms of university GPA of freshmen and the probability of graduating within six years. Morell's work will be extended in several ways. More than one cohort of students will be used. Second, the research tests whether differences exist between students who come from different high schools, after controlling for students' observable traits such as high school GPA and family background. Third, the paper tests whether high school resources such as the teacher-pupil ratio and teachers' credentials are related to student outcomes at UCSD. To the best of our knowledge this paper is the first to model individual students' university GPA as a function of family background and the traits of the high school attended.

III. Data

Detailed data on undergraduates who enrolled at UCSD between Fall 1991 and Fall 1993 were obtained from the UCSD Student Information System; other student information was obtained from the Central Processing data files of the Educational Testing Service. Our sample includes all students who enrolled at UCSD during this period who had previously attended California public high schools. We excluded transfer students who had transferred to UCSD from a community college or another four-year post-secondary institution. These information sources, provide for each student a detailed picture of enrollment, GPA by quarter, field of study, and background information including the Educational Testing Service (ETS) code of the high school last attended and the student's scores in the math and verbal sections of the Scholastic Aptitude (SAT) test.

These data were merged with information on the California public high schools from which the students graduated. Our main source of information was the California Department of Education, which provided information from the 1992–93 school year on the level and composition of enrollment at each high school and number and types of teachers. The same source provided two measures of the socioeconomic background of the students at each school for 1994. The first, which we use in most of our regressions, is the proportion of students in the school's attendance area who were receiving Aid to Families with Dependent Children (AFDC). The second, which we use in the appendix, is the proportion of students who in 1994 received free or reduced cost meals.

A third source of data was a special tabulation of data from the 1990 Census of Population, which provides detailed demographic traits for each school district in California. The two variables from this dataset which we use in the main tables are median household income in the school district in 1989 and the proportion of the population older than 20 in the school district who held a Bachelor's degree or higher in 1990.

A fourth set of data, provided by the ETS, contains ETS school codes, average 1992 SAT scores (math and verbal) and the number of students writing the SAT, for each high school in California. These latter variables are used in regressions in the appendix.

For details on how the various data were merged, see the appendix.

Although some of our information on schools and school districts come from different years, we believe that the data will provide a highly accurate picture of school resources and demographic traits for the high schools attended by UCSD freshmen. Most of the data corresponds to the 1992–93 school year, which is close to the time when our three cohorts of freshmen are assumed to have graduated (Spring 1991 through Spring 1993). The district-level demographic data correspond to 1989 or 1990, depending on the variable, although the school-level information on AFDC usage and meal assistance correspond to the 1994 school year. Because the demographic traits of an area are unlikely to change radically over three or four years, we believe that these proxies for neighborhood characteristics should deliver a quite accurate depiction of the environment in which each UCSD undergraduate attended high school.

The means and standard deviations of the variables used in the main tables appear in Table A1 in the appendix. The student population at UCSD differs from that of the nation at large. The student population is over-represented by Asian students and under-represented by all other races and ethnicities, including whites. This reflects both differences between the population of San Diego county and the country as a whole, and the relatively selective nature of UCSD's undergraduate program. For instance, according to 1990 Census data, 6.0 percent of the San Diego County population is black, which is about half the national average. But blacks constitute only 2.3 percent of the UCSD sample, reflecting the competitive nature of UCSD admissions, in spite of affirmative action programs that were in place during all years represented in the study. Therefore, the results reported below do not necessarily reflect patterns at the national level, because of regional variations in the demographic background of students, and because selection into UCSD is nonrandom. In particular, one referee suggested that some schools might send their best students to UCSD, although other schools might send their best students to Berkeley and their second best to UCSD. If this selection is correlated in any way with the level of school resources at the two schools, the observed correlation between high school resources and GPA at UCSD would give a biased picture of the average effect of school inputs on university GPA. However, given that this is the first research that to our knowledge has simultaneously modeled university GPA as a function of personal, high school and neighborhood traits, we believe that the study makes a tangible contribution.

IV. Reduced Form Estimates of the Total Effect of School Resources on University GPA

In this section we estimate reduced form models of cumulative university GPA. In other words, we do not include high school GPA or SAT scores as explanatory variables in these regressions, because these variables themselves represent endogenous outcome variables; by including them we risk understating the total effect of school resources on students' university GPA.

The dependent variable in this analysis is the cumulative university GPA, on a scale of 0 to 4, for the latest quarter in which the student was enrolled. Because our latest transcript data are from Spring Quarter 1996, and the students in the sample first enrolled between 1991 and 1993, most students were still enrolled at this time.

Our chief goals in this section will be to test whether personal background is related to GPA, whether the demographic characteristics of the area in which the student attended high school influence his or her university GPA, and whether measures of school resources are significantly related to GPA. We add demographic characteristics of the neighborhood and school based on the common observation in the school quality literature that the student's peer group can influence his or her rate of learning.[2] We choose three measures of demographic traits: the proportion of students at the school who received AFDC in 1994, the proportion of the population above age 20 in the school district who had Bachelor's degrees or higher in 1990, and the median household income in the school district in 1989, in thousands of dollars. We use three measures of school resources: the ratio of full-time equivalent teachers to pupils in the high school, the average years of teacher experience, and the proportion of teachers in the school who hold a Master's degree or higher.

Before proceeding with detailed regression analysis, we began with two-way plots of the relation between university GPA and these six variables.[3] Each of the plots using one of the three socioeconomic variables suggested that university GPA rises with socioeconomic status of the school and neighborhood populations. The relationship, if any, between university GPA and the school inputs was somewhat less clear.

2. See Coleman et al. (1966) and Hanushek (1986).
3. Due to space constraints, these plots are not shown, but are available from the authors, or online from http://weber.ucsd.edu/~jbetts.

The strongest link that emerged between GPA and school resources was for average teacher experience, where a positive relationship was readily apparent. Simple regressions of mean GPA on a constant and one school trait at a time support the conclusion that with the exception of teacher experience, school inputs are not nearly as strongly correlated with GPA as are the measures of the socioeconomic traits of the school and neighborhood population. The t-statistics on the six explanatory variables in the series of regressions were: AFDC (-9.2), median income (7.6), adults with college degrees (8.4), teacher-pupil ratio (2.9), teacher experience (6.6), teachers with postgraduate degrees (-1.2).

Of course, none of these relationships may persist after we properly control for the student's personal background. For this reason we now turn to more formal regression analysis using the individual student, rather than the school, as the unit of observation.

Because GPA is likely to vary by year of study, it follows that we should condition on the year of study in which the final measure of GPA is observed. We include dummy variables to indicate observations corresponding to the second through fifth years of study; students for whom the last year of available data is the first year of study serve as the control group. A student's GPA may depend on the difficulty and/or grading standards in the field in which the student decides to major. Therefore, we also condition on the major in which the student is enrolled (Engineering, Science, Arts, Humanities, and Social Sciences, with Undeclared or Missing as the omitted category). We include the following variables to capture the personal background of the student: dummy variables for men, blacks, Hispanics, Asians, and Other (nonwhite) Races, a dummy variable for foreign students, and dummy variables indicating five categories for the parents' income, in 1992 prices, with the omitted category being parental income below \$25,000.[4] The justification for inclusion of these variables stems from the frequent observation in the school quality literature that personal and family background tend to be highly correlated with student achievement, measured in terms of test scores.[5]

We estimate by Ordinary Least Squares (OLS) the following model, where i denotes the student, j denotes the school, GPA refers to the last observation on university *GPA, BACK* is a vector containing the aforementioned family background variables, and the *YEAR* and *MAJOR* variables are the controls for year of study and major, and m is the number of majors minus one:

$$(1) \quad GPA_{ij} = c + \sum_{t=2}^{5} YEAR_{ij}^{t}\chi^{t} + BACK_{ij}\Delta + \sum_{k=1}^{m} MAJOR_{ij}^{k}\theta^{k} + \varepsilon_{ij}$$

Table 1, Column 1, shows the results for this basic model. Most of the family background variables are highly significant. Males tend to have a significantly lower

4. Because students reported parental income in the year in which they applied for admission to UCSD, the raw income variable was converted to 1992 prices using the Consumer Price Index in order to make this variable comparable across the three cohorts of students. Parental income is available for the vast majority of students who came directly from high school to the university, as the admissions form requests this information to be provided if the parent(s) claimed the applicant as a dependent for income tax purposes in the year in which the application was made.

5. See for instance the review by Hanushek (1986). Similarly, Taubman (1989) documents the frequent empirical finding that family income has a significant positive impact on years of schooling completed.

GPA than females, on the order of 0.06 point. Ethnic minorities also obtain significantly lower GPAs than do whites, with the largest gap arising between black and white students. Of course, we must be circumspect in interpreting correlation between GPA and gender or ethnicity as causal.[6] Foreign students obtain slightly lower GPAs than do citizens, but as will be shown this effect is no longer significant at 5 percent once we estimate more complex models. Parental income is a highly significant predictor of GPA: students whose parents' income was in the range of \$50,000 to \$199,999 tended to have a higher Grade Point Average than did students from less affluent backgrounds. Interestingly, the impact of family income appears to taper off among students whose parents' income was \$200,000 or higher—the GPA of these students was not significantly different from students with parental income below \$25,000.[7] As hypothesized, the student's GPA varies significantly across majors, with the lowest GPAs occurring among engineering and science students, and the highest GPAs occurring among those enrolled in arts and humanities.[8] This model tends to confirm the test score literature, which has found that personal background is an important determinant of academic achievement.

Table 1, Column 2 shows the econometric results when we simultaneously control for the socioeconomic environment of the school along with personal background, including major and year of study. The student's GPA tends to drop as the proportion of students in his or her high school who received AFDC rises. Similarly, the proportion of the adult population with Bachelor's degrees or higher is positively and significantly related to GPA. Median household income in the district was not significantly related to GPA, though, after controlling for personal background. As shown in the final row of the table, the hypothesis that these three variables can be jointly excluded is strongly rejected.[9]

These findings are significant in two senses. First, they support previous findings in the literature that a student's environment, or peer group, affects learning. Even after controlling for parental income and the student's gender and race, these variables appear to have an independent effect on how well the student does at university. Second, the predicted impact of marginal changes in the AFDC and college education variables is quite high. Consider an increase in either variable of 0.20, in other words, a 20 percent increase. As shown in Table A1, this represents a rise of approximately two standard deviations for either variable. Such a rise in the AFDC variable is

6. One possibility that we have not fully explored is whether variations in GPA across ethnicity reflect variations in the types of courses which students take. The set of dummy variables that we have included for major field of study cannot control fully for unobserved variations in the degree of difficulty of courses taken by each student.

7. Experimentation with different ways of categorizing parental income—for instance making \$150,000 the lower bound for the highest income category—tended to show the same decline in the impact of family income on GPA at higher income levels. Graphical analysis confirmed that the impact of parental income appeared to level off or decline beyond \$150,000 or \$200,000.

8. We also attempted a more detailed model that controlled for 32 fields of study instead of 5 broad majors. But an F-test of the simpler model with broad majors was strongly retained against the more detailed model with department of study. Therefore we chose the simpler model in this and later tables.

9. We chose these three measures of demographic background for the school because they capture the median socioeconomic status, and at the same time characterize the two extremes of the socioeconomic distribution. Of course, these and other socioeconomic indicators are quite highly correlated, so that it would be unwise to claim more than that the socioeconomic environment matters, in plausible directions.

Table 1
Reduced Form Models of University GPA

Variable	1	2	3	4	5	6
Constant	2.8678	2.8342	2.8611	2.6931	2.9329	2.8617
	(94.78)	(64.47)	(34.85)	(42.94)	(56.21)	(27.08)
Male	−0.0645	−0.0681	−0.0680	−0.0685	−0.0687	−0.0690
	(−4.79)	(−5.09)	(−5.08)	(−5.12)	(−5.14)	(−5.17)
Black	−0.4005	−0.3630	−0.3629	−0.3617	−0.3611	−0.3582
	(−9.30)	(−8.43)	(−8.43)	(−8.41)	(−8.39)	(−8.34)
Hispanic	−0.3268	−0.2893	−0.2890	−0.2852	−0.2890	−0.2822
	(−14.69)	(−12.85)	(−12.82)	(−12.65)	(−12.84)	(−12.53)
Asian	−0.1241	−0.1140	−0.1143	−0.1139	−0.1108	−0.1103
	(−8.24)	(−7.56)	(−7.57)	(−7.56)	(−7.34)	(−7.31)
Other race	−0.1343	−0.1256	−0.1254	−0.1269	−0.1216	−0.1211
	(−3.23)	(−3.04)	(−3.04)	(−3.08)	(−2.95)	(−2.94)
Foreign	−0.0481	−0.0393	−0.0396	−0.0387	−0.0381	−0.0377
	(−2.04)	(−1.68)	(−1.69)	(−1.66)	(−1.63)	(−1.61)
Income						
25–49.999K	−0.0413	−0.0362	−0.0362	−0.0355	−0.0358	−0.0346
	(−2.19)	(−1.93)	(−1.93)	(−1.89)	(−1.91)	(−1.85)
50–74.999K	0.0381	0.0340	0.0339	0.0340	0.0348	0.0348
	(2.04)	(1.83)	(1.83)	(1.83)	(1.87)	(1.88)
75–99.999K	0.0617	0.0519	0.0519	0.0511	0.0501	0.0483
	(2.99)	(2.52)	(2.52)	(2.49)	(2.44)	(2.35)
100–199.999K	0.1057	0.0853	0.0852	0.0831	0.0829	0.0788
	(4.99)	(4.02)	(4.02)	(3.92)	(3.91)	(3.72)
200K–Higher	0.0504	0.0223	0.0223	0.0167	0.0212	0.0135
	(1.08)	(0.48)	(0.48)	(0.36)	(0.46)	(0.29)
Last year enroll = 2	0.0292	0.0242	0.0245	0.0195	0.0199	0.0128
	(0.78)	(0.65)	(0.65)	(0.52)	(0.53)	(0.34)
Last year enroll = 3	0.3111	0.3069	0.3070	0.3022	0.3028	0.2953
	(10.78)	(10.71)	(10.71)	(10.54)	(10.56)	(10.30)

Last year enroll = 4	0.3798	0.3762	0.3765	0.3714	0.3714	0.3642
	(13.46)	(13.42)	(13.43)	(13.24)	(13.25)	(12.98)
Last year enroll = 5	0.2711	0.2724	0.2727	0.2690	0.2672	0.2616
	(8.40)	(8.50)	(8.51)	(8.40)	(8.34)	(8.17)
Engineering	−0.1181	−0.1097	−0.1096	−0.1079	−0.1090	−0.1060
	(−6.49)	(−6.06)	(−6.05)	(−5.96)	(−6.03)	(−5.86)
Science	−0.0619	−0.0546	−0.0545	−0.0521	−0.0538	−0.0495
	(−3.57)	(−3.17)	(−3.16)	(−3.02)	(−3.12)	(−2.87)
Arts	0.1014	0.1003	0.1005	0.1013	0.1012	0.1032
	(2.07)	(2.06)	(2.07)	(2.08)	(2.08)	(2.13)
Humanities	0.0513	0.0578	0.0579	0.0602	0.0616	0.0664
	(1.32)	(1.50)	(1.50)	(1.56)	(1.60)	(1.73)
Social science	0.0177	0.0221	0.0222	0.0213	0.0232	0.0227
	(0.89)	(1.12)	(1.13)	(1.08)	(1.18)	(1.16)
Proportion on AFDC		−0.3867	−0.3856	−0.3478	−0.4135	−0.3691
		(−4.64)	(−4.62)	(−4.13)	(−4.94)	(−4.38)
Median household income		−0.0003	−0.0003	−0.0004	−0.0004	−0.0007
		(−0.38)	(−0.44)	(−0.48)	(−0.50)	(−0.85)
Proportion with Bachelor's		0.2855	0.3015	0.2706	0.3265	0.3687
		(3.91)	(3.59)	(3.70)	(4.42)	(4.23)
Teacher-pupil ratio			−0.7315			−2.1183
			(−0.39)			(−1.08)
Average teacher experience				0.0082		0.0109
				(3.15)		(4.03)
Proportion teachers graduate degree					−0.1803	−0.2477
					(−3.50)	(−4.53)
R-squared	0.1366	0.1487	0.1487	0.1502	0.1506	0.1533
Adjusted R-squared	0.1336	0.1452	0.1451	0.1466	0.1469	0.1494
P-value 1 vs. current		0.00000	0.00000	0.00000	0.00000	0.00000
P-value 2 vs. 6						0.00000

Note: Sample size is 5,623. *T*-statistics appear in parentheses.

predicted to lead to a drop in the student's university GPA of 0.77 point; a rise of 20 percent in the proportion of the adult population with a Bachelor's or higher is predicted to lead to a 0.57 point increase in the student's GPA. These changes are quite large, especially compared to the predicted changes in GPA associated with changes in family income.

Having established that both personal background and measures of the socioeconomic environment of the school and school district are significantly linked to students' university performance, we now test whether school resources influence how well students fare once they reach university. To begin with, we estimate a fixed effect variant of (1), in which each school is assigned its own intercept:

$$(2) \quad GPA_{ij} = \sum_{k=1}^{n} SCHOOL_{ij}^{k}\alpha_k + \sum_{t=2}^{5} YEAR_{ij}^{t}\chi^{t} + BACK_{ij}\Delta + \sum_{k=1}^{m} MAJOR_{ij}^{k}\theta^{k} + \varepsilon_{ij}$$

where n is the number of schools and m is the number of major fields of study, less one. In this equation, the $SCHOOL_{ij}$ variables are dummy variables equal to one if $j = k$, and 0 otherwise. In our regression sample, we have students from 498 California public high schools. We test that the GPA of all students is the same, regardless of school attended, after controlling for the basic variables in (1):

$$(3) \quad H_0\colon \alpha_1 = \alpha_2 = \alpha_3 \cdots = \alpha_{498}$$

When the model was estimated, the probability value (p-value) on this hypothesis was 0.0000, indicating that students from different high schools obtain significantly different GPAs once they arrive at university. Of course, this finding does not prove that public high schools differ in quality. These measured differences could simply be capturing neighborhood effects. With this problem in mind, the model in Table 1, Column 2, with its three measures of neighborhood traits, was also estimated with fixed effects. The null hypothesis that all high schools are equal in quality was again rejected, with a p-value of 0.0047. Thus, although the measured interschool differences are weaker after we control for neighborhood traits, the interschool differences remain highly significant.[10]

Given evidence that California high schools differ in quality, we now ask whether proxies for school spending can explain any of these differences, after controlling for personal background and environmental/peer effects proxied by the three measures of the socioeconomic environment. As mentioned above, we use three measures of school resources: the ratio of full-time equivalent teachers to pupils in the high school, the average years of teacher experience, and the proportion of teachers

10. Another possible criticism of the interpretation that "schools differ in quality" is that our school fixed effects are merely detecting interpersonal differences, because many schools in our UCSD sample are represented by just one or two students. Accordingly, Regressions 1 and 2 in Table 1 were both reestimated with school fixed effects after first removing cases in which fewer than three students had attended the school. In this smaller sample, of 5,442 students representing 372 schools, the null that all schools are identical is in both cases rejected with a p-value of 0.0000.

in the school who hold a Master's degree or higher. All three of these variables capture important aspects of school spending.[11]

Columns 3–5 of Table 1 list the results when Model 2 is reestimated with the addition of one of these three measures of school resources. Column 6 shows the results when all three measures of school inputs are added to Model 2 at once. As shown in Column 3, the teacher-pupil ratio is not significantly related to a student's GPA once he or she arrives at university. In contrast, students who attended schools with more highly experienced teachers perform significantly better at university. Although highly significant, the effect is meaningful but not large in a policy sense: an increase of ten years in teachers' average experience is predicted to increase a student's GPA at university by 0.08 point. Finally, GPA is significantly and *negatively* related to the proportion of teachers in the student's high school who held Master's or Ph.D. degrees.[12] As shown in the final column of the table, these results persist when all three measures of school inputs are added together to Model 2.

We undertook numerous tests of robustness. First, we reestimated the models using random effects, to take account of the fact that there are in many cases repeated observations for each school. These models led to highly similar conclusions in terms of level of significance of the key regressors, and the size of their coefficients.[13] In the paper we present OLS results rather than random effects results, though, as Hausman tests suggested that the latter were inconsistent, with p-values of 0.002 or less.

Second, we tested for nonlinear effects of school resources by adding squares of each school input to Models 3–6 in Table 1. A reasonable assumption is that due to diminishing returns the marginal impact of school inputs may decrease as the input rises, which would result in a negative coefficient on the square of the input. In results that are not shown, such a pattern emerges for the teacher-pupil ratio and teacher experience, but in neither case is the pattern significant. For the teacher education variable, the opposite pattern obtains, but again is not significant. We conclude from this table that nonlinearities are not an important aspect of the data. It remains possible that nonlinearities in the relation are obscured by the use of school-average data.

Third, following the suggestion of a referee, we reran Table 1, Column 6 on the subsamples corresponding to each of the five college majors. In these smaller sam-

11. Each of the three policies—smaller classes, more highly educated and more highly experienced teachers—represents a policy change that will create new costs for a school. Classroom expenditures, which consist largely of teacher salaries, will move proportionately with the teacher-pupil ratio. On average, classroom expenditures account for about 60 percent of spending in American public schools. (National Center for Education Statistics 1991, page 154.) Nonclassroom expenditures can also rise with an increase in the teacher-pupil ratio if such a change dictates the building of new classrooms. Betts (1996a) estimates from the March 1993 Current Population Survey that teachers with Master's degrees command approximately a 17 percent wage premium over teachers without postgraduate degrees. Similarly, most teacher salary contracts stipulate that salaries should rise with years of teaching experience.

12. The graphs of mean GPA by school had suggested such a negative relationship, but it was not significant.

13. The regressors typically had t-statistics which were 5 to 10 percent lower in the random effects specification, but the levels of statistical significance were unchanged in that the absolute t-statistic of the regressors in no case crossed the 5 percent significance level of 1.96. The coefficients were little changed by the introduction of random effects, with changes typically occurring in the second or third significant digit. For example, in Table 1, Column 6, the key coefficient (and t-statistic) on average teacher experience became 0.0114 (3.85) in the random effects specification.

ples coefficients sometimes became insignificant, but in 83 percent of cases coefficients maintained the same sign as in the regression using the full sample. Most of the sign reversals occurred in the subsamples of arts and humanities students, which were very small. In no subsample did a coefficient reverse sign with a t-statistic above, or even close to, 1.96. We conclude that the observed effects of family, peer group, and high school are quite similar across the five college majors.

As a final check on the results, we tested for robustness of the coefficients on the school resources to omitted peer group or neighborhood effects. In particular, does the positive coefficient on teacher experience merely reflect a positive correlation between teacher experience and the socioeconomic traits of the neighborhood? In Table 1, we have attempted to control for this possibility using three socioeconomic indicator variables. We did not include more because the three we have used capture traits of the median and both the upper and lower ends of the socioeconomic spectrum. Adding more background controls, which tended to be highly correlated with the three measures already in use, might suggest that individual measures of socioeconomic status of the school's and the area's populations did not matter, when in fact socioeconomic status did matter. Accordingly, we assembled a matrix of 24 variables designed to capture the traits of the student body at each high school and the school neighborhood, along with the 24 squares of these variables. We performed a factor analysis of these 48 variables to identify the principal components of the data. We chose the first 14 principal components, as these captured fully 90 percent of the variation in the 48 variables. We then repeated the main models in Table 1, replacing the three measures of socioeconomic background with the 14 principal components from the factor analysis. The results appear in Table A2 in the appendix, where we also list the 24 variables used.

If the three measures of school resources are merely capturing unmeasured socioeconomic traits of the student body, then in these specifications, the t-statistics on the school resource variables should fall toward zero. Comparing the results in Table A2 with Models 3–6 in Table 1, we instead find that the coefficients and t-statistics on the school inputs are remarkably robust. In particular, the coefficient and level of significance on average teacher experience are very little changed. This finding increases our confidence that the results do not suffer heavily from omitted variable bias.[14]

How are we to interpret the diverse results from Table 1? First, the finding that the high school teacher-pupil ratio is not significantly related to GPA is typical of the literature. Betts (1996b) finds that studies that have measured the teacher-pupil ratio at the level of the actual school attended have found no link to the student's ultimate educational attainment. However, several studies that use district- or state-level measures of class size as proxies for the class size enjoyed by the individual student do show significant links.[15] Hanushek (1996) surveys 377 studies of test

14. As an even more stringent test for omitted background variables, we added the 24 variables and their squares directly to Model 4 in Table A2, in place of the principal components. The results were quite similar, with coefficients (and t-statistics) on the three measures of school resources as follows: teacher-pupil ratio -1.4757 (-0.60), teacher experience 0.0092 (2.74) and the proportion of teachers with a graduate degree -0.2320 (-3.57).

15. Similarly, Betts (1995) and Grogger (1996) find little or no significant link between the teacher-pupil ratio at the individual's high school and subsequent earnings.

scores and the teacher-pupil ratio and finds that only 15 percent show a positive and significant link; 13 percent of the studies found a *negative* and significant link, and fully 72 percent of the studies revealed no significant relation. Similarly, in a detailed study of American and Asian public schools, Stevenson and Stigler (1992) find that Asian students regularly outperformed American students on standardized tests, yet often were taught in much larger classes.

However, a second possible explanation is that there is too little variation in the teacher-pupil ratio in California's high schools to enable us to detect a positive effect, even if it exists. As shown in Table A1 in the appendix, the coefficient of variation, that is, the ratio of the standard deviation to the mean, is only 0.1 in this sample, compared to 0.14 for teacher experience and 0.23 for the teacher education variable.

As with the results for the teacher-pupil ratio, the finding of a perverse but significant relationship between the proportion of teachers with postgraduate degrees and university GPA accords with much of the test score literature. Hanushek (1996) reports that 5 percent of 171 test score studies found a similarly negative and significant relation, although only 9 percent reported a positive and significant relation. In addition, another 27 percent of the studies reported a negative but insignificant relationship. One reason why teacher education may not have a large impact on student outcomes is that requirements in some locales that teachers obtain a Master's degree within a certain time after beginning teaching merely induces teachers to obtain the "certification," without regard to the program contents. Similarly, the typically automatic pay hike that awaits teachers who obtain a postgraduate degree may induce similar forms of "credentialism."[16,17]

Finally, how should we interpret the one case in which school spending appears to be significantly and positively related to subsequent performance in university by students? Are more highly experienced teachers necessarily better teachers? One possible concern is the direction of causation. As documented in Chapter 4 of Murnane et al. (1991), in some school districts teachers with seniority have first rights to job openings in other schools in the district. This could potentially lead to reverse causation: more experienced teachers might migrate to jobs in the schools that have the best prepared students because these are considered plum jobs. As shown in the school quality literature, often the main characteristic of such schools is the relatively high socioeconomic status of students.[18]

We have already shown in Table A2 that the coefficient on teacher experience is robust to inclusion of a large number of socioeconomic traits of the school population and the neighborhood. But in order to test this possibility of reverse causation further,

16. Chapters 7 and 8 of Murnane et al. (1991) argue that both of these policies—mandatory Master's degrees for teachers in states such as California and New York, and automatic pay hikes for those teachers who acquire a Master's degree—create the wrong set of incentives for teachers.

17. Betts (1996b) finds that most papers which have tested for a link between earnings of students after they leave school and the level of education of their teachers have found no link. None of the three previously published papers that have modeled educational attainment as a function of teacher education have found a significant link. For similar evidence using the National Longitudinal Survey of Young Women, see Betts (1996c).

18. Teachers may prefer to teach at such schools not only because students are better prepared academically, but because violence is less prevalent at such schools. Grogger (1997) establishes that teachers appear to command slightly higher salaries at violence-ridden schools, perhaps because higher salaries help to retain teachers who are working under difficult circumstances.

Table 2
Models with Alternative Measures of Teacher Experience

Variable	1	2	3
Average teacher experience	0.0082		0.0155
	(3.15)		(2.84)
Experience in district		0.0043	−0.0067
		(2.04)	(−1.52)
R-squared	0.1502	0.1493	0.1506
Adjusted R-squared	0.1466	0.1457	0.1468

Note: Sample size is 5,623. *T*-statistics appear in parentheses. Other regressors are as shown in Table 1.

Table 2 provides models that employ various measures of teacher experience. If the positive link between students' subsequent performance at university and teacher experience merely reflects the migration of teachers with seniority to the best schools in the district as jobs open up, then only teacher experience *gained inside the school district* should matter. (Experience outside the district will not typically increase the teacher's seniority within the district.) The first model in the table replicates Model 4 from Table 1. If the observed positive correlation between teacher experience and students' GPA at university merely reflects seniority-based movement of teachers, then we would expect that the average years of teacher experience *in the district* should be more highly linked to GPA than total years. But as shown in Model 2, this is not the case.

Models 1 and 2 are nonnested hypotheses, which cannot be tested against each other using traditional methods. Instead, in Model 3, we create an artificially nested model that includes both measures of teacher experience. Davidson and MacKinnon (1981) developed the *J*-test as a specification test for one model against a nonnested alternative. In our case, the *t*-statistic on one experience variable is interpreted as a specification test of the model that contains the second measure of experience, and vice versa. If the added experience variable is significant, it suggests that the original model is misspecified because it cannot explain some of the variation in GPA captured by the experience variable used in the alternative model. By this criterion, the model which hypothesizes that it is teachers' experience within the district that matters is rejected at less than 5 percent; the model which hypothesizes that total teacher experience determines university GPA is retained at better than 10 percent. We conclude that the model that uses total experience is correctly specified, although the model that assumes that only experience within the district matters is misspecified.[19]

The models and tests represented in Table 2 suggest that teaching experience outside the district is at least as valuable as teaching experience within the district.

19. An alternate way of specifying 3 is to enter experience within and outside the district as separate regressors. As implied by the above statement, at the 10 percent level there is no statistically significant difference between the effectiveness of teaching experience within and outside the school district.

This increases our confidence that the positive link observed between university GPA and high school teachers' experience represents a genuine causal relationship, rather than reverse causation related to seniority-based teacher transfers into the best schools.[20]

The conclusion from this section is that some school resources, in particular teacher experience, might be correlated with students' subsequent GPA at university. But personal background and the socioeconomic traits of the school and school district population are much more important determinants of students' GPA at university.

V. Can High School Resources and Demographic Traits Improve Predictions of University GPA?

In the previous section the GPA models did not include high school GPA or SAT scores as predictors of university GPA. Because it is likely that better schools produce students who obtain higher SAT scores, higher grade school GPA and higher university GPA, including the former two potentially endogenous variables as regressors would have reduced the coefficients on the measures of school resources. The models in the previous section are thus specified correctly if one's goal is to measure the *total* effect of school spending on university achievement.

But universities can and do use high school GPA and SAT scores in their admission decisions. Therefore, it is important to study whether these variables predict university GPA well, and whether personal background, school traits, or demographic characteristics can improve predictions of students' university GPA. To answer these questions, in this section we estimate models of university GPA which condition upon high school GPA and SAT scores.

We begin the formal regression analysis with a variant of (1):

$$(4)\quad GPA_{ij} = c + HSGPA_{ij}\beta + SATM_{ij}\gamma_m + SATV_{ij}\gamma_v + \sum_{t=2}^{5} YEAR_{ij}^{t}\chi^{t} + BACK_{ij}\Delta + \sum_{k=1}^{m} MAJOR_{ij}^{k}\theta^{k} + \varepsilon_{ij}$$

This equation adds the high school GPA, and the math and verbal SAT scores (HSGPA, SATM and SATV respectively) to (1). This equation allows us to test a number of hypotheses:

i) Do high school GPA (HSGPA) and SAT scores predict GPA at UCSD well? H_0: $\beta = \gamma_m = \gamma_v = 0$

ii) Does personal background provide information beyond that obtainable from high school GPA and test scores? H_0: $\Delta = 0$

Column 1 in Table 3 shows the above model estimated without the personal background variables. As suggested by Morell's (1993b) analysis of UCSD's freshman

20. Furthermore, the robustness tests in Table A2 in the appendix suggest that teacher experience is not proxying for unmeasured socioeconomic traits of the student body or neighborhood.

Table 3
Predicting University GPA using High School GPA, Test Scores, and Background Information on the High School and Student

Variable	1	2	3	4
Constant	−0.2758	−0.1297	−0.2260	−0.1680
	(−3.38)	(−1.45)	(−2.38)	(−1.31)
High school GPA	0.5272	0.5097	0.5450	0.5537
	(29.22)	(27.36)	(28.90)	(29.38)
SAT math	0.0008	0.0009	0.0007	0.0007
	(9.90)	(10.52)	(8.33)	(7.85)
SAT verbal	0.0009	0.0008	0.0007	0.0007
	(13.07)	(10.24)	(9.33)	(9.02)
Male		−0.0862	−0.0788	−0.0768
		(−6.67)	(−6.14)	(−6.00)
Black		−0.0553	−0.0304	−0.0259
		(−1.34)	(−0.74)	(−0.63)
Hispanic		−0.0598	−0.0277	−0.0224
		(−2.74)	(−1.26)	(−1.03)

Asian		−0.0900	−0.0846	−0.0809
		(−6.44)	(−6.07)	(−5.81)
Other Race		−0.0209	−0.0188	−0.0133
		(−0.55)	(−0.50)	(−0.35)
Proportion on AFDC			−0.2166	−0.2112
			(−2.84)	(−2.75)
Median household income			0.0003	−0.0001
			(0.36)	(−0.14)
Proportion with Bachelor's			0.3804	0.4795
			(5.67)	(6.02)
Teacher-pupil ratio				−2.0372
				(−1.14)
Average teacher experience				0.0102
				(4.15)
Proportion Teachers Graduate degree				−0.2903
				(−5.81)
R-squared	0.2825	0.2991	0.3112	0.3165
Adjusted R-squared	0.2809	0.2962	0.3079	0.3129
P-Value 1 vs. current P-Value		0.00000	0.00000	0.00000
Previous vs. current			0.00000	0.00000

Note: Sample size is 5,470. *T*-statistics appear in parentheses. Other regressors not shown correspond to those shown in Table 1.

class of 1990, both SAT scores and high school GPA are highly predictive of university GPA. The null hypothesis in i) above is strongly rejected (p-value = 0.0000). Nonetheless, fully 72 percent of the observed variation in university GPAs remains to be explained. Furthermore, a one-to-one correspondence does not exist between high school and university GPA. The model suggests that a one-point increase in HSGPA translates into an increase in university GPA of only 0.53 point.[21]

We next test the hypothesis that the student's personal background does not add any explanatory power to the model once HSGPA and SAT scores are included. Column 2 of Table 3 shows that the student's gender and race continue to be highly significant predictors of GPA. (In coefficients not shown, to some extent parental income also remains significant.) An F-test for the joint exclusion of these personal traits rejected the null with a p-value of 0.0000, as shown in the penultimate row of the table.[22]

It is noteworthy that after we condition on high school achievement, there is no longer a statistically significant difference between blacks and whites or between "other races" (nonwhite) and whites. Significant differences persist between whites on the one hand and Hispanics and Asians on the other, although the size of the coefficients drop considerably. This finding is similar to that by O'Neill (1990) and Neal and Johnson (1996) that earnings differences between blacks and whites are largely accounted for by precollege factors such as test scores.

We next test whether, conditional upon high school achievement and personal background, high schools "matter." In the model:

$$(5) \quad GPA_{ij} = \sum_{j=1}^{n} SCHOOL_{ij}^{k}\alpha_k + HSGPA_{ij}\beta + SATM_{ij}\gamma_m + SATV_{ij}\gamma_v + \sum_{t=2}^{5} YEAR_{ij}^{t}\chi^{t} + BACK_{ij}\Delta + \sum_{k=1}^{m} MAJOR_{ij}^{k}\theta^{k} + \varepsilon_{ij}$$

we test that

$$(6) \quad H_0\colon \alpha_1 = \alpha_2 = \alpha_3 \cdots = \alpha_n.$$

21. Of course, this apparent dissipation of GPA once the student arrives at university in part reflects collinearity between HSGPA and the SAT scores. Reestimation of the model without SAT scores increased the coefficient on HSGPA moderately, to 0.6. As shown in Table A1, high school GPA is on average about 0.8 point higher than the university GPA.

22. As we have postulated, because the three measures of high school success are positively correlated with university GPA, the signs and size of the coefficients on the measures of personal background tend to be smaller than what was found in the reduced form models in Table 1, Column 1.

The hypothesis in (6) was strongly rejected, with a p-value of 0.0000.[23] We thus conclude that students from certain high schools obtain a significantly higher university GPA than do other students, even after controlling for the student's high school GPA, SAT scores and observable personal characteristics.

Accordingly, in Column 3 of Table 3 we add the three measures of the demographic background of people in the school area, and then in Column 4 we also add the three measures of school resources. As shown in the penultimate row in the table, tests of each model against the more complex model to its right in all cases strongly reject the simpler model. The coefficients and t-statistics on the school and neighborhood traits in both Models 3 and 4 are quite similar to our earlier results.

By how much do the GPA predictions improve once we add the measures of school resources and demographic background of the school? The change in the R^2 provides a rough guide. Model 1, which conditions only on high school performance and major and year of study at university, accounts for about 28 percent of the variation in GPA. As we add the measures of personal background, demographic traits and high school resources, we succeed in explaining slightly over 31 percent of the observed variation.[24] Despite the modest improvement in explanatory power, the size of the predicted impact on GPA is in some cases meaningful. For instance, Model 4 predicts that if two otherwise identical students come from school districts in which 20 percent and 50 percent of the adult population held four-year or higher college degrees respectively, the latter student will obtain a university GPA of (0.5–0.2) * (0.3804) or about 0.11 grade point higher.

An alternative approach to improving predictions of student performance is to condition the model not on specific traits of the high school, but on the fixed effects for the schools themselves. When we ran the fixed effect model the R^2 on Model 2 in Table 3 rose from 0.2962 to 0.3984.[25] Thus adding separate intercepts for each school can account for roughly another 9–10 percent of the variation in undergraduate GPAs.

VI. Conclusion

Existing research on the determinants of school quality tends to focus on models of test scores or earnings. Very little attention has been given to the impact

23. As before, we reestimated this model after removing schools attended by fewer than 3 students, in a bid to minimize the possibility that what we are identifying is not school effects so much as individual effects. We obtained the same p-value for the hypothesis in (6).

24. Of course, it would be wrong to conclude from this comparison that the variables in the simple model in Column 1 "explain" 28/3 = 9.3 times as much of the variation in GPAs as do the additional regressors added in Column 4. This interpretation is incorrect because the change in R^2 depends on which set of regressors—the new regressors in Column 4 or the regressors in Column 1, are added first. Our goal here is simply to estimate how much additional variation in GPA can be explained by personal, school and demographic factors, given that administrators are already "controlling" for high school GPA and SAT scores in the admissions process.

25. When we repeated this exercise on the subsample of schools for which we had three or more students, in order to ensure that the school fixed effects were identifying a school effect rather than an individual effect, the R^2 rose from 0.2963 to 0.3856.

of schools on educational achievement. Betts (1996b) finds only 14 published articles dealing with the link between school resources and educational attainment. In most cases, the only way in which attainment has been measured is in terms of years of education completed.

This paper has used a different measure of success in postsecondary education: the student's GPA. This approach is useful given evidence that university GPA is linked to students' subsequent earnings.

We find that personal background, including sex, ethnicity, and family income, is significantly linked to university GPA. We also find that the socioeconomic environment of the school matters. We tested that three measures of school resources, the teacher-pupil ratio, the average experience of teachers, and the proportion of teachers with advanced degrees, influenced students' subsequent performance in university. For the teacher-pupil and teacher education variables, we could find no evidence of a positive and significant link with university GPA. We in fact found a significant and negative link between GPA and the proportion of high school teachers with advanced degrees. Although surprising at first, these findings are in accordance with much of the earlier literature on test scores. However, we did find a positive and significant link between teacher experience and the student's GPA. We expressed concerns that this apparent relationship might reflect selection of teachers with seniority into job vacancies in the schools with the best prepared students, which are typically in more affluent areas. But two sets of robustness tests suggest that this sort of reverse causation is not at work.

We have also tested whether college administrators' use of high school GPA and SAT scores to predict success in university is valid. High school GPA and SAT scores are indeed strongly linked to university GPAs. However, we also find strong evidence that GPA predictions could be improved by including measures of the student's personal background, the socioeconomic environment of the school, and some measures of school resources. For instance, women tend to obtain higher GPAs than men.[26] Similarly, students who attended a school in which a high proportion of students' families received AFDC, or a school in an area where only a small proportion of adults hold college degrees, obtain significantly lower GPAs in university than other students. However, the gains in predictive power we obtained are fairly modest. Addition of controls for personal background, school resources and the school's socioeconomic environment explained an additional 3 percent of the variation in university GPAs beyond the simple model. An alternative method for improving forecasts of university GPA would be to model GPA with separate intercepts for each high school. Such a fixed effect model can explain about 10 percent of the variation in university GPA beyond the simple model.

These results should be of interest to two policy communities. First, for university administrators, our results suggest that although high school grades and test scores are good predictors of university GPA, more complex models that condition on personal background and school and neighborhood traits can significantly improve predictions of student's university GPA. Even after controlling for high school grades

26. However, we caution the reader that omitted variable bias may be responsible for some of the observed variations across gender and ethnicity.

and test scores, students from certain underrepresented groups, and from schools located in economically disadvantaged areas, are likely to obtain lower grades in university.

We wish to stress, though, that GPA is only one measure of adult success. Our data provide no evidence on how much two different students would gain in earnings from attending university. Although a student from a disadvantaged area may indeed obtain a lower GPA at university than an otherwise identical student from an affluent area, the *gain* in earnings from attending university could be larger for the student from the economically disadvantaged area.

Second, our results should be of interest to public school administrators and to those studying the economics of education. The research provides evidence that schools with more highly experienced teachers produce graduates who perform significantly better at university. But the effects are moderate in size: an extra ten years of teaching experience among teachers at the student's school is associated with a university GPA which is approximately 0.1 point higher. Our results for the other two measures of school inputs conform more closely to the test-score literature, which has typically found little evidence that greater school resources improve student performance. Overall, our estimates suggest that in California, variations in family background and in the socioeconomic environment of the school play far more crucial roles in determining student outcomes in university than do variations in school resources.

Appendix

Merging the Datas

Merging the school-level data with the individual student data proceeded in several steps. First, the California Department of Education datas, for which high school names, city, zip code and the California ''CDS'' code were available, were merged with each other using the CDS school-level codes. Second, the ETS data containing SAT scores and ETS school codes was merged with the California data by matching for the CDS school district code and the school name, which were available in both datas. Next, the Census of Population data by school district were merged using the CDS district-level codes. Finally, the resulting data containing information on individual high schools and the demographic traits of the populations in the corresponding school districts was merged with the data on UCSD undergraduates, using the ETS school codes. This process did not provide a match for every UCSD student who had attended a public school, because of missing data in the ''bridging'' data which contained both ETS codes and CDS codes. Consequently, in cases where we had initially failed to match the high school attended by a UCSD freshman to the California Department of Education data, we manually matched schools using information on the school's name, and the city and county in which they were located. These pieces of information were available both from the UCSD Registrar's data and the California Department of Education data. We achieved matches for 98.6 percent of the schools and 99.7 percent of the freshmen who had attended California public high schools.

Table A1
Means and Standard Deviations of Variables Used in Tables 1 to 4

Variable	Number	Mean	Standard
University GPA	5,623	3.033	0.516
High school GPA	5,602	3.875	0.338
SAT math	5,491	618.880	84.621
SAT verbal	5,491	514.163	89.876
Male	5,623	0.487	0.500
Black	5,623	0.023	0.151
Hispanic	5,623	0.103	0.304
Asian	5,623	0.338	0.473
Other race	5,623	0.025	0.156
Foreign	5,623	0.095	0.293
Income 25–49.999K	5,623	0.190	0.392
Income 50–74.999K	5,623	0.198	0.398
Income 75–99.999K	5,623	0.147	0.354
Income 100–199.999K	5,623	0.138	0.345
Income 200K–higher	5,623	0.020	0.141
Last year enroll = 2	5,623	0.057	0.232
Last year enroll = 3	5,623	0.327	0.469
Last year enroll = 4	5,623	0.433	0.496
Last year enroll = 5	5,623	0.123	0.328
Engineering	5,623	0.226	0.419
Science	5,623	0.243	0.429
Arts	5,623	0.018	0.133
Humanities	5,623	0.030	0.170
Social science	5,623	0.156	0.363
Proportion on AFDC	5,623	0.098	0.095
Median household income	5,623	41.938	12.318
Proportion with bachelor's degree	5,623	0.279	0.123
Teacher-pupil ratio	5,623	0.041	0.004
Proportion teachers graduate degree	5,623	0.559	0.128
Average teacher experience	5,623	17.963	2.560
Average teacher experience in district	5,623	15.312	3.044
Average teacher experience outside district	5,623	2.651	1.557

Table A2
Repetition of GPA Models from Table 1 with Principal Components from a Factor Analysis of Demographic Background as Additional Controls

Variables	1	2	3	4
Teacher-pupil Ratio	−1.6900			−2.0016
	(−0.86)			(−1.00)
Average teacher experience		0.0067		0.0096
		(2.34)		(3.21)
Proportion teachers graduate			−0.1567	−0.2194
Degree			(−2.86)	(−3.81)
R-squared	0.1573	0.1580	0.1584	0.1603
Adjusted R-squared	0.1573	0.1527	0.1531	0.1546

Note: Sample size is 5,537. *T*-statistics appear in parentheses. Other regressors not listed in the table are as listed in Table 1, Models 3 through 5, and the first 14 principal components from a factor analysis of 24 variables and their squares, each of which is meant to serve as a proxy for the socioeconomic setting of the school. These 24 variables included the AFDC (1994) variable, median household income (1989) in the school district, and the proportion of the adult population in the district with Bachelor's degrees or higher (1990), which correspond to the three variables that we have already used in the main regressions. We also added the following district-level variables derived from the 1990 Census: the proportion of the population over 20 with high school diplomas, the proportion with some college, median house values, median gross rent, and the proportions of the population which are "urban-inside urbanized area," "rural-farm," and "ruralnonfarm," with "urban-outside urbanized area" as the excluded category. All of these variables refer to 1990. We also included the following characteristics of the students attending the given high school: the proportion of students in the attendance area receiving free or reduced cost meals, the proportion of the student body which was in the category of Limited English Proficiency, four variables indicating the proportion of the student body which was black, Asian, Hispanic, or other nonwhite, the proportion of the graduates from the high school who had completed all courses required for entrance to the University of California or the California State University systems, the high-school dropout rate, average scores on the verbal and math components of the SAT, the number of students who wrote the SAT exams as a proportion of Grade 12 enrollment, and the proportions of the Grade 10 class which had scored 5 or 6 on the reading, writing and math components of the California Learning Assessment System (CLAS). (Information provided to us by the California Department of Education states that the CLAS scores range from 1 to 6, with 1, the lowest level, showing little or no evidence of understanding or achievement, and 6, the highest level, indicating exemplary student work.) All of these latter variables refer to the 1992–93 school year, except for the meal assistance variable, which refers to the 1994–95 school year.

References

Betts, Julian R. 1995. "Does School Quality Matter? Evidence from the National Longitudinal Survey of Youth." *Review of Economics and Statistics* 77:231–50.

———. 1996a. "Do School Resources Matter Only for Older Workers?" *Review of Economics and Statistics* 78:638–52.

———. 1996b. "Is There a Link between School Inputs and Earnings? Fresh Scrutiny of an Old Literature." In *Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success,* ed. G. Burtless, 141–91. Washington, D.C.: Brookings Institution.

———. 1996c. "The Impact of School Resources on Women's Earnings and Educational

Attainment: Findings from the National Longitudinal Survey of Young Women.'' Discussion Paper 96–24, Department of Economics, University of California, San Diego.

Card, David, and Alan B. Krueger. 1992. ''Does School Quality Matter? Returns to Education and the Characteristics of Public Schools in the United States.'' *Journal of Political Economy* 100:1–40.

Coleman, James et al. 1966. *Equality of Educational Opportunity.* Washington, D.C.: GPO.

Davidson, Russell, and James G. MacKinnon. 1981. ''Several Tests for Model Specification in the Presence of Alternative Hypotheses.'' *Econometrica* 49:781–93.

Filer, Randall K. 1983. ''Sexual Differences in Earnings: The Role of Individual Personalities and Tastes.'' *Journal of Human Resources* 18(1):82–99.

Grogger, Jeff. 1996. ''Does School Quality Explain the Recent Black/White Wage Trend?'' *Journal of Labor Economics* 14:231–53.

———. 1997. ''Local Violence, Educational Attainment and Teacher Pay.'' National Bureau of Economic Research Working Paper 6003, April.

Grogger, Jeff, and Eric Eide. 1995. ''Changes in College Skills and the Rise in the College Wage Premium.'' *Journal of Human Resources* 30(2):280–310.

Hanushek, Eric A. 1986. ''The Economics of Schooling: Production and Efficiency in Public Schools.'' *Journal of Economic Literature* 24:1141–77.

———. 1989. ''The Impact of Differential Expenditures on School Performance.'' *Educational Researcher:* 45–51, 62.

———. 1991. ''When School Finance 'Reform' May Not be Good Policy.'' *Harvard Journal on Legislation* 28:423–56.

———. 1996. ''School Resources and Student Performance.'' In *Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success,* ed. G. Burtless, 43–73. Washington, D.C.: Brookings Institution.

Heckman, James, Anne Layne-Farrar, and Petra Todd. 1996. ''Does Measured School Quality Really Matter? An Examination of the Earnings-Quality Relationship.'' In *Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success,* ed. G. Burtless, 192–289. Washington, D.C.: Brookings Institution.

Hungerford, Thomas and Gary Solon. 1987. ''Sheepskin Effects in the Returns to Education.'' *Review of Economics and Statistics* 69:175–77.

Jones, Ethel B., and John D. Jackson. 1990. ''College Grades and Labor Market Rewards.'' *Journal of Human Resources* 25(2):253–66.

Loury, Linda D., and David Garman. 1995. College Selectivity and Earnings.'' *Journal of Labor Economics* 13:289–308.

Morell, Darlene. 1993a. ''Admissions Criteria, Enrollment Management, and the Probability of College Completion: A Validity Study. Manuscript.'' Student Research and Information, Student Affairs, University of California, San Diego.

———. 1993b. '''Weighing' Admissions Decisions at UCSD: How Valid is the Academic Index?'' A Case Study. Manuscript, Student Research and Information, Student Affairs, University of California, San Diego.

Murnane, Richard J., Judith D. Singer, John B. Willett, James J. Kemple, and Randall J. Olsen. 1991. *Who Will Teach? Policies that Matter.* Cambridge, Mass.: Harvard University Press.

National Center for Education Statistics. 1991. *Digest of Education Statistics 1991.* Washington, D.C.: GPO.

Neal, Derek A. and William R. Johnson. 1996. ''The Role of Premarket Factors in Black-White Wage Differences.'' *Journal of Political Economy* 104:869–95.

O'Neill, June. 1990. ''The Role of Human Capital in Earnings Differences between Black and White Men.'' *Journal of Economic Perspectives* 4:25–45.

Raymond, Raymond. 1968. ''Determinants of the Quality of Primary and Secondary Public Education in West Virginia.'' *Journal of Human Resources* 3(4):450–70.

Stevenson, Harold W., and James W. Stigler. 1992. *The Learning Gap: Why our Schools are Failing and What We Can Learn from Japanese and Chinese Education.* New York: Summit Books.

Taubman, Paul, 1989. ''Role of Parental Income in Educational Attainment.'' *American Economic Review* 79(May):57–61.

Wise, David A. 1975. ''Academic Achievement and Job Performance.'' *American Economic Review* 65:350–66.