ESTIMATING THE PAYOFF TO ATTENDING A MORE SELECTIVE COLLEGE: AN APPLICATION OF SELECTION ON OBSERVABLES AND UNOBSERVABLES*

STACY BERG DALE AND ALAN B. KRUEGER

Estimates of the effect of college selectivity on earnings may be biased because elite colleges admit students, in part, based on characteristics that are related to future earnings. We matched students who applied to, and were accepted by, similar colleges to try to eliminate this bias. Using the College and Beyond data set and National Longitudinal Survey of the High School Class of 1972, we find that students who attended more selective colleges earned about the same as students of seemingly comparable ability who attended less selective schools. Children from low-income families, however, earned more if they attended selective colleges.

A burgeoning literature has addressed the question, "Does the 'quality' of the college that students attend influence their subsequent earnings?"[1] Obtaining accurate estimates of the payoff to attending a highly selective undergraduate institution is of obvious importance to the parents of prospective students who foot the tuition bills, and to the students themselves. In addition, because college selectivity is typically measured by the average characteristics (e.g., average SAT score) of classmates, the literature is closely connected to theoretical and empirical studies of peer group effects on individual behavior. And with higher education making up 40 percent of total educational expenditures in the United States (see U. S. Department of Education [1997, Table 33]), understanding the impact of selective colleges on students' labor market outcomes is central for understanding the role of human capital.[2]

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1. The modern literature began with papers by Hunt [1963], Solmon [1973], Wales [1973], Solmon and Wachtel [1975], and Wise [1975], and has undergone a recent renaissance, with papers by Brewer and Ehrenberg [1996], Behrman et al. [1996], Daniel, Black, and Smith [1997], Kane [1998], and others. See Brewer and Ehrenberg [1996, Table 1] for an excellent summary of the literature.

2. This figure ignores any earnings students forgo while attending school, which would increase the relative cost of higher education.

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Past studies have found that students who attended colleges with higher average SAT scores or higher tuition tend to have higher earnings when they are observed in the labor market. Attending a college with a 100 point higher average SAT is associated with 3 to 7 percent higher earnings later in life (see, e.g., Kane [1998]). As Kane notes, an obvious concern with this conclusion is that students who attend more elite colleges may have greater earnings capacity regardless of where they attend school. Indeed, the very attributes that lead admissions committees to select certain applicants for admission may also be rewarded in the labor market. Most past studies have used Ordinary Least Squares (OLS) regression analysis to attempt to control for differences in student attributes that are correlated with earnings and college qualities. But college admissions decisions are based in part on student characteristics that are unobserved by researchers and therefore not held constant in the estimated wage equations; if these unobserved characteristics are positively correlated with wages, then OLS estimates will overstate the payoff to attending a selective school. Only three previous papers that we are aware of have attempted to adjust for selection on unobserved variables in estimating the payoff to attending an elite college. Brewer, Eide, and Ehrenberg [1999] use a parametric utility maximizing framework to model students' choice of schools, under the assumption that all students can attend any school they desire. Behrman, Rosenzweig, and Taubman [1996] utilize data on female twins to difference out common unobserved effects, and Behrman et al. [1996] use family variables to instrument for college choice. Our paper complements these previous approaches.

This paper employs two new approaches to adjust for nonrandom selection of students on the part of elite colleges. In one approach, we only compare college selectivity and earnings among students who were *accepted and rejected* by a comparable set of colleges, and are comparable in terms of observable variables. In the second approach, we hold constant the average SAT score of the schools to which each student applied, as well as the average SAT score of the school the student actually attended, the student's own SAT score, and other variables. The second approach is nested in the first estimator. Conditions under which these estimators provide unbiased estimates of the payoff to college quality are discussed in the next section. In short, if admission to a college is based on a set of variables that are observed by the admissions committee and later by the econometrician (e.g., student SAT), *and* another set of variables that is observed by the admissions committee (e.g., an assessment of student motivation) but not by the econometrician, and if both sets of variables influence earnings, then looking within matched sets of students who were accepted and rejected by the same groups of colleges can help overcome selection bias.

Barnow, Goldberger, and Cain [1981] point out that, "Unbiasedness is attainable when the variables that determined the assignment rule are known, quantified, and included in the [regression] equation." Our first estimator extends their concept of "selection on the observables" to "selection on the observables and unobservables," since information on the unobservables can be inferred from the outcomes of independent admission decisions by the schools the student applied to. The general idea of using information reflected in the outcome of independent screens to control for selection bias may have applications to other estimation problems, such as estimating wage differentials associated with working in different industries or sizes of firms (where hiring decisions during the job search process provide screens) and racial differences in mortgage defaults (where denials or acceptances of applications for loans provide screens).[3]

We provide selection-corrected estimates of the payoff to school quality using two data sets: the College and Beyond Survey, which was collected by the Andrew W. Mellon Foundation and analyzed extensively in Bowen and Bok [1998], and the National Longitudinal Survey of the High School Class of 1972 (NLS-72). Two indirect indicators of college quality are used: college selectivity, as measured by a school's average SAT score, and net tuition. Our primary finding is that the monetary return to attending a college with a higher average SAT score falls considerably once we adjust for selection on the part of the college. Nonetheless, we still find a substantial payoff to attending schools with higher net tuition.

Although most of the previous literature has implicitly assumed that the returns to attending a selective school are homogeneous across students, an important issue in interpreting our findings is that there may be heterogeneous returns to students

3. Braun and Szatrowski [1984] use a related idea to evaluate law school grades across institutions by comparing the performance of students who were accepted at a common set of law schools but attended different schools.

for attending the same school. Some students may benefit more from attending a highly selective (or unselective) school than others. For example, a student intent on becoming an engineer is likely to have at least as high earnings by attending Pennsylvania State University as Williams College, since Williams does not have an engineering major. In this situation, if students are aware of their own potential returns from each school to which they are admitted, they could be expected to sort into schools based on their expected utility from attending that school, as in the Roy model of occupational choice. In other words, the students who chose to go to less selective schools may do so because they have higher returns from attending those schools (or because there are nonpecuniary benefits from attending those schools); however, the average students might not have a higher return from attending a less selective school over a more selective one. Nonetheless, contrary to the previous literature, this interpretation implies that attending a more selective school is not the income-maximizing choice for all students. Instead, students would maximize their returns by attending the school that offers the best fit for their particular abilities and desired future field of employment.

I. A Stylized Model of College Admissions, Attendance, and Earnings

For most students, college attendance involves three sequential choices. First, a student decides which set of colleges to apply to for admission. Second, colleges independently decide whether to admit or reject the student. Third, the student and her parents decide which college the student will attend from the subset of colleges that admitted her. To start, we consider a highly stylized model of both admissions and the labor market as a benchmark for analysis. We discuss departures from these simplifying assumptions later on.

Assume that colleges determine admissions decisions by weighing various attributes of students. A National Association for College Admission Counseling [1998] survey, for example, finds that admissions officers consider many factors when selecting students, including the students' high school grades and test scores, and factors such as their essays, guidance counselor and teacher recommendations, community service, and extracurricular activities. Next, we assume that each college uses a threshold to make admissions decisions. An applicant who possesses characteristics that place him or her above the threshold is accepted; if not, he or she is rejected. Additionally, idiosyncratic luck may enter into the admission decision.

The characteristics that the admissions committee observes and bases admission decisions on can be partitioned into two sets of variables: a set that is subsequently observed by researchers and a set that is unobserved by researchers. The observable set of characteristics includes factors like the student's SAT score and high school grade point average (GPA), while the unobservable set includes factors like assessments of the student's motivation, ambition, and maturity as reflected in her essay, college interview, and letters of recommendation. For simplicity, assume that X_1 is a scalar variable representing the observable characteristics the admissions committee uses and X_2 is an unobservable (to the econometrician) variable that also enters into the admissions decisions.[4] We assume that each college, denoted j, uses the following rule to admit or reject applicant i:

$$\text{(1)}\quad \text{if } Z_{ij} = \gamma_1 X_{1i} + \gamma_2 X_{2i} + e_{ij} > C_j \text{ then admit to college } j$$
$$\text{otherwise reject applicant at college } j,$$

where Z_{ij} is the latent quality of the student as judged by the admissions committee, e_{ij} represents the idiosyncratic views of college j's admission committee, γ_2 and γ_2 are the weights placed on student characteristics in admission decisions, and C_j is the cutoff quality level the college uses for admission.[5] The term e_{ij} represents luck and idiosyncratic factors that affect admission decisions but are unrelated to earnings. We assume that e_{ij} is independent across colleges. By definition, more selective colleges have higher values of C_j.

Now suppose that the equation linking income to the students' attributes is

$$\text{(2)}\qquad \ln W_i = \beta_0 + \beta_1 SAT_{j^*} + \beta_2 X_{1i} + \beta_3 X_{2i} + \epsilon_i,$$

where SAT_{j^*} is the average SAT score of matriculants at the college student i attended, X_1 and X_2 are the characteristics used

4. In terms of the previously defined sets of variables, one could think of X_1 and X_2 as a linear combination of the variables in each set, where the weights were selected to give X_1 and X_2 the coefficients in equation (1).

5. We ignore the possibility of wait listing the student.

by the admission committee to determine admission, and ε_i is an idiosyncratic error term that is uncorrelated with the other variables on the right-hand side of (2). Since individual SAT scores are a common X_1 variable, SAT_{j*} can be thought of as the mean of X_1 taken over students who attend college $j*$. The parameter β_1, which may or may not equal zero, represents the monetary payoff to attending a more selective college. This coefficient would be greater than zero if peer groups have a positive effect on earnings potential, for example.

In practice, researchers have been forced to estimate a wage equation that omits X_2:

$$\text{(3)} \qquad \ln W_i = \beta_0' + \beta_1' SAT_{j*} + \beta_2' X_{1i} + u_i.$$

Even if students randomly select the college they attend from the set of colleges that admitted them, estimation of (3) will yield biased and inconsistent estimates of β_1 and β_2. Most importantly for our purposes, if students choose their school randomly from their set of options, the payoff to attending a selective school will be biased upward because students with higher values of the omitted variable, X_2, are more likely to be admitted to, and therefore attend, highly selective schools. Since the labor market rewards X_2, and school-average SAT and X_2 are positively correlated, the coefficient on school-average SAT will be biased upward. The coefficient on X_1 can be positively or negatively biased, depending on the relationship between X_1 and X_2. Also notice that the greater the correlation between X_1 and X_2, the lesser the bias in β_1'.

Formally, the coefficient on school-average SAT score is biased upward in this situation because $E(\ln W_i | SAT_{j*}, X_{1i}) = \beta_0 + \beta_1 SAT_{j*} + \beta_2 X_{1i} + E(u_i | X_{1i}, \gamma_1 X_{1i} + \gamma_2 X_{2i} + e_{ij*} > C_{j*})$. The expected value of the error term (u_i) is higher for students who were admitted to, and therefore more likely to attend, more selective schools.[6]

If, conditional on gaining admission, students choose to attend schools for reasons that are independent of X_2 and ε, then students who were accepted and rejected by the same set of schools would have the same expected value of u_i. Consequently, our proposed solution to the school selection problem is to include an unrestricted set of dummy variables indicating groups of stu-

6. A classic reference on selection bias is Heckman [1979].

dents who received the same admissions decisions (i.e., the same combination of acceptances and rejections) from the same set of colleges. Including these dummy variables absorbs the conditional expectation of the error term if students randomly choose to attend a school from the set of schools that admitted them. Moreover, even if college matriculation decisions (conditional on acceptance) are related to X_2, controlling for dummies indicating whether students were accepted and rejected by the same set of schools absorbs some of the effect of the unobserved X_2.

To see why controlling for dummies indicating acceptance and rejection at a common set of schools partially controls for the effect of X_2, consider two colleges that a subset of students applied to with admission thresholds $C_1 < C_2$. College 2 is more selective than college 1. If the selection rule in equation (1) did not depend on a random factor, then it would be unambiguous that students who were admitted to college 1 and rejected by college 2 possessed characteristics such that $C_1 < \gamma_1 X_1 + \gamma_2 X_2 < C_2$. As C_1 approaches C_2, the (weighted) sum of the students' observed and unobserved characteristics becomes uniquely identified by observations on acceptance and rejection decisions.[7] Because X_1 is included in the wage equation, the omitted variables bias would be removed if $(\gamma_1 X_1 + \gamma_2 X_2)$ were held constant. If enough accept and reject decisions over a fine enough range of college selectivity levels are observed, then students with a similar history of acceptances and rejections will possess essentially the same average value of the observed and unobserved traits used by colleges to make admission decisions. Thus, even if matriculation decisions are dependent on X_2, we can at least partially control for X_2 by grouping together students who were admitted to and rejected by the same set of colleges and including dummy variables indicating each of these groups in the wage regression. Notice that to apply this estimator, it is necessary for students to be accepted by a diverse set of schools and for some of those students to attend the less selective colleges and others the more selective colleges from their menu of choices.

If the admission rule used by colleges depended only on X_1, and if X_1 were included in the wage equation, we would have a case of "selection on the observables" (see Barnow, Cain, and

7. Dale and Krueger [1999] provide a set of simulations to illustrate these results. The fact that idiosyncratic factors affect colleges' admissions decisions through e_{ij} complicates but does not distort this result.

Goldberger [1981]). In this case, however, we have "selection on the observables and unobservables" since X_{2i} and e_{ij} are also inputs into admissions decisions. Nonetheless, we can control for the bias due to selective admissions by controlling for the schools at which students were admitted.

In reality, all students do not apply to the same set of colleges, and it is probably unreasonable to model students as randomly selecting the school they attend from the ones that accepted them. A complete model of the two-sided selection that takes place between students and colleges is beyond the scope of the current paper, but it should be stressed that our selection correction still provides an unbiased estimate of β_1 if students' school enrollment decisions are a function of X_1 or any variable outside the model.

The critical assumption is that students' enrollment decisions are uncorrelated with the error term of equation (2) and X_2. If the decision rule students use to choose the college they attend from their set of options is related to their value of X_2, then the bias in the within-matched-applicant model depends on the coefficient from a hypothetical regression of the average SAT score of the school the student attends on X_2, conditional on X_1 and dummies indicating acceptance and rejection from the same set of schools. It is possible that selection bias could be exacerbated by controlling for such matched-applicant effects. Griliches [1979] makes this point in reference to twins models of earnings and education. In the current context, however, if students apply to a fine enough range of colleges, the accept/reject dummies would control for X_2, and the within-matched-applicant estimates would be unbiased even if college choice on the part of students depended in part on X_2.

Also notice that it is possible that the effect of attending a highly selective school varies across individuals. If this is the case, equation (2) should be altered to give an "i" subscript on the coefficient on *SAT*. Students in this instance would be expected to sort among selective and less selective colleges based on their potential returns there, assuming that they have an idea of their own personalized value of β_{1i}. In such a situation, our estimate of the return to attending a selective school can be biased upward or downward, and it would not be appropriate to interpret our estimate of β_1 as a causal effect for the average student.

Another factor that would be expected to influence student matriculation decisions is financial aid. By definition, merit aid is related to the school's assessment of the student's potential. Past studies have found that students are more likely to matriculate to schools that provide them with more generous financial aid packages (see, e.g., van der Klaauw [1997]). If more selective colleges provide more merit aid, the estimated effect of attending an elite college will be biased upward because relatively more students with higher values of X_2 will matriculate at elite colleges, even conditional on the outcomes of the applications to other colleges. The relationship between aid and school selectivity is likely to be quite complicated, however. Breneman [1994, Chapter 3], for example, finds that the middle ranked liberal arts colleges provide more financial aid than the highest ranked and lowest ranked liberal arts colleges. If students with higher values of X_2 are more likely to attend less selective colleges because of financial aid, the selectivity bias could be negative instead of positive.

Finally, an alternative though related approach to modeling unobserved student selection is to assume that students are knowledgeable about their academic potential, and reveal their potential ability by the choice of schools they apply to. Indeed, students may have a better sense of their potential ability than college admissions committees. To cite one prominent example, Steven Spielberg was rejected by both the University of Southern California and the University of California Los Angeles film schools, and attended California State Long Beach [Grover 1998]. It is plausible that students with greater observed and unobserved ability are more likely to apply to more selective colleges. In this situation, the error term in equation (3) could be modeled as a function of the average SAT score (denoted AVG) of the schools to which the student applied: $u_i = \tau_0 + \tau_1 AVG_i + v_i$. If v_i is uncorrelated with the SAT score of the school the student attended, we can solve the selection problem by including AVG in the wage equation. We call this approach the "self-revelation" model because individuals reveal their unobserved quality by their college application behavior. When we implement this approach, we include dummy variables indicating the number of schools the students applied to (in addition to the average SAT score of the schools), because the number of applications a student submits may also reveal unobserved student traits, such as their ambition and patience. Notice that the average SAT score of the schools the student applied to, and the number of applications they submitted, would be absorbed by including unrestricted dummies indicating students who were accepted and rejected by the same sets of schools; therefore, the self-revelation model is nested in our first model.

It is useful to illustrate the difference between the matched applicant model and the self-revelation models with an example. In the matched-applicant model, we compare two students who were each accepted by both a highly selective college, such as the University of Pennsylvania, and a moderately selective college, such as Pennsylvania State University, but one student chose to attend Penn and the other Penn State. It is possible that the reason the student chose to attend Penn State over Penn (or vice versa) is also related to that student's earnings potential: those who chose to attend a less selective school from their options may have greater or lower earnings potential. In this case, estimates from the matched-applicant model would be biased upward or downward, depending on whether more talented students chose to matriculate to more or less selective colleges conditional on their options. In the self-revelation model, we compare two students who applied to—but were not necessarily accepted by—both Penn and Penn State. In this case, the student who attended Penn State is likely to have been rejected by Penn; as a result, the student who attended Penn State is likely to be less promising (as judged by the admissions committee) than the one who attended the University of Pennsylvania. If it is generally true that students with higher unobserved ability are more likely to be accepted by (and therefore more likely to attend) the more selective schools, the self-revelation model is likely to overstate the return to school selectivity.

II. Data and Comparison to Previous Literature

The College and Beyond (C&B) Survey is described in detail in Bowen and Bok [1998, Appendix A]. The starting point for the database was the institutional records of students who enrolled in (but did not necessarily graduate from) one of 34 colleges in 1951, 1976, and 1989. These institutional records were linked to a survey administered by Mathematica Policy Research, Inc. for the Andrew W. Mellon Foundation in 1995–1997 and to files provided by the College Entrance Examination Board (CEEB) and the Higher Education Research Institute (HERI) at the University of California, Los Angeles. We focus here on the 1976 entering cohort. While survey data are available for 23,572 students from this cohort, we exclude students from four historically black colleges and universities. For most of our analysis we restrict the sample to full-time workers, defined as those who responded "yes" to the C&B survey question, "Were you working full-time for pay or profit during all of 1995?" The 30 colleges and universities in our sample, as well as their average SAT scores and tuition, are listed in Appendix 1. Our final sample consists of 14,238 full-time, full-year workers.

The C&B institutional file consists of information drawn from students' applications and transcripts, including variables such as students' GPA, major, and SAT scores. These data were collected for all matriculants at the C&B private schools; for the four public universities, however, data were collected for a subsample of students, consisting of all minority students, all varsity letter-winners, all students with combined SAT scores of 1,350 and above, and a random sample of all other students. We constructed weights that equaled the inverse probability of being sampled from each of the C&B schools. Thus, our weighted estimates are representative of the population of students who attend the colleges and universities included in the C&B survey.

The C&B institutional data were linked to files provided by HERI and CEEB. The CEEB file contains information from the Student Descriptive Questionnaire (SDQ), which students fill out when they take the SAT exam. We use students' responses to the SDQ to determine their high school class rank and parental income. The file that HERI provided is based on data from a questionnaire administered to college freshman by the Cooperative Institutional Research Program (CIRP). We use this file to supplement C&B data on parental occupation and education.

Finally, the C&B survey data consist of the responses to a questionnaire that most respondents completed by mail in 1996, although those who did not respond to two different mailings were surveyed over the phone. The survey response rate was approximately 80 percent. The survey data include information on 1995 annual earnings, occupation, demographics, education, civic activities, and satisfaction.[8] Importantly for our purposes,

8. The C&B survey asked respondents to report their 1995 pretax annual earnings in one of the following ten intervals: less than $1,000; $1,000–$9,999; $10,000–$19,999; $20,000–$29,999; $30,000–$49,999; $50,000–$74,999; $75,000–$100,000; $100,000–$149,999; $150,000–$199,999; and more than $200,000. We converted the lowest nine earnings categories to a cardinal scale by assigning values equal to the midpoint of each range, and then calculated the

early in the questionnaire respondents were asked, "In rough order of preference, please list the other schools you seriously considered."[9] Respondents were then asked whether they applied to, and were accepted by, each of the schools they listed.[10] By linking the school identifiers to a file provided by HERI, we determined the average SAT score of each school that each student applied to. This information enabled us to form groups of students who applied to a similar set of schools and received the same admissions decisions (i.e., the same combination of acceptances and rejections). Because there were so many colleges to which students applied, we considered schools equivalent if their average SAT score fell into the same 25 point interval. For example, if two schools had an average SAT score between 1200 and 1225, we assumed they used the same admissions cutoff. Then we formed groups of students who applied to, and were accepted and rejected by, "equivalent" schools.[11] To probe the robustness of our findings, however, we also present results in which students were matched on the basis of the *actual* schools they applied to, and on the basis of the colleges' *Barron's* selectivity rating.

Table I illustrates how we would construct five groups of matched applicants for fifteen hypothetical students. Students A and B applied to the exact same three schools and were accepted and rejected by the same schools, so they were paired together. The four schools to which students C, D, and E applied were sufficiently close in terms of average SAT scores that they were

natural log of earnings. For workers in the topcoded category, we used the 1990 Census (after adjusting the Census data to 1995 dollars) to calculate mean log earnings for college graduates age 36–38 who earned more than $200,000 per year. The value we assigned for the topcode may be somewhat too low, because income data from the 1990 Census were also topcoded (values of greater than $400,000 on the 1990 Census were recoded as the state median of all values exceeding $400,000) and because students who attended C&B schools may have higher earnings than the population of all college graduates.

9. Students who responded to the C&B pilot survey were not asked this question, and therefore are excluded from our analysis.

10. Students could have responded that they couldn't recall applying or being accepted, as well as yes or no. They were asked to list three colleges other than the one they attended that they seriously considered. In addition, prior to the question on schools the student seriously considered, respondents were asked "which school did you *most* want to attend, that is, what was your first choice school?" If that school was different from the school the student attended, there was a follow-up question that asked whether the student applied to their first-choice school, and whether they were accepted there. Consequently, information was collected on a maximum of four colleges to which the student could have applied, in addition to the college the student attended.

11. Students who applied to only one school were not included in these matches.

TABLE I
ILLUSTRATION OF HOW MATCHED-APPLICANT GROUPS WERE CONSTRUCTED

		Student applications to college							
		Application 1		Application 2		Application 3		Application 4	
Student	Matched-applicant group	School average SAT	School admissions decision	School average SAT	School admissions decision	School average SAT	School admissions decision	School average SAT	School admissions decision
Student A	1	1280	Reject	1226	Accept*	1215	Accept	na	na
Student B	1	1280	Reject	1226	Accept	1215	Accept*	na	na
Student C	2	1360	Accept	1310	Reject	1270	Accept*	1155	Accept
Student D	2	1355	Accept	1316	Reject	1270	Accept*	1160	Accept
Student E	2	1370	Accept*	1316	Reject	1260	Accept	1150	Accept
Student F	Excluded	1180	Accept*	na	na	na	na	na	na
Student G	Excluded	1180	Accept*	na	na	na	na	na	na
Student H	3	1360	Accept	1308	Accept*	1260	Accept	1160	Accept
Student I	3	1370	Accept*	1311	Accept	1255	Accept	1155	Accept
Student J	3	1350	Accept	1316	Accept*	1265	Accept	1155	Accept
Student K	4	1245	Reject	1217	Reject	1180	Accept*	na	na
Student L	4	1235	Reject	1209	Reject	1180	Accept*	na	na
Student M	5	1140	Accept	1055	Accept*	na	na	na	na
Student N	5	1145	Accept*	1060	Accept	na	na	na	na
Student O	No match	1370	Reject	1038	Accept*	na	na	na	na

* Denotes school attended.
na = did not report submitting application.
The data shown on this table represent hypothetical students. Students F and G would be excluded from the matched-applicant subsample because they applied to only one school (the school they attended). Student O would be excluded because no other student applied to an equivalent set of institutions.

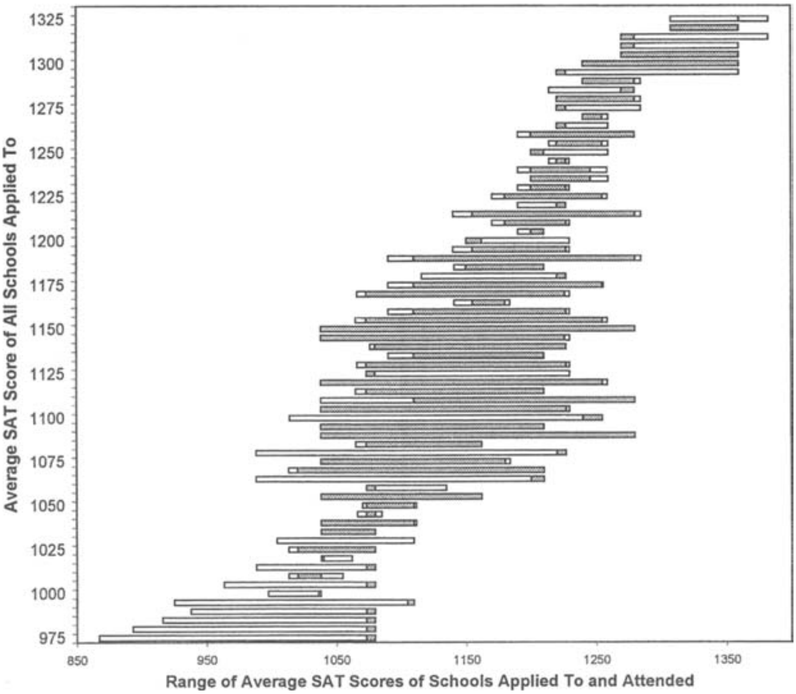

FIGURE I
Range of Schools Applied to and Attended by Most Common Sets of Matched Applicants

Each bar represents the range of the average SAT scores of the schools that a given set of matched applicants applied to; the shaded area represents the range of schools that students in each set attended. Only matched sets that represent fifteen or more students are shown. A total of 3,038 students are represented on the graph.

considered to use the same admission standards; because these students received the same admissions decisions from comparable schools, they were categorized as matched applicants. Students were not matched if they applied to only one school (students F and G), or if no other student applied to a set of schools with similar SAT scores (student O). Five dummy variables would be created indicating each of the matched sets.

Figure I illustrates the college application and attendance patterns of the most common sets of matched applicants (i.e., those sets that include at least fifteen students) in the C&B data set. The length of the bars indicates the range of schools to which each set of matched students applied, and the shaded area of each bar represents the range of schools that each set of students actually attended. The average range of school-average SAT scores of all students who were accepted by at least two schools was 145 points, approximately equal to the spread between Tufts and Yale. If students applied to only a narrow range of schools, then measurement error in the classification of school selectivity will be exacerbated in the matched-applicant models. In subsection III.B we present some estimates of the likely impact of this potential bias.

Table II provides weighted and unweighted means and standard deviations for individuals who were employed full-time in 1995. Everyone in the sample attended a C&B school as a freshman but did not necessarily graduate from the school (or from any school). Nearly 70 percent of students listed at least one other school they applied to in addition to the school they attended. Among students who were accepted by more than one school, 62 percent chose to attend the most selective school to which they were admitted. We were able to match 44 percent of the students with at least one other student in the sample on the basis of the schools that they were accepted and rejected by. Summary statistics are also reported for the subsample of matched applicants. It is clear that the schools in the C&B sample are very selective. The students' average SAT score (Math plus Verbal) exceeds 1,100. Over 40 percent of the sample graduated in the top 10 percent of their high school class. The mean annual earnings in 1995 for full-time, full-year workers was $84,219, which is high even for college graduates.

Because the C&B data set represents a restricted sample of elite schools and is not nationally representative, we compared the payoff to attending a more selective school in the C&B sample to corresponding OLS estimates from national samples. When we replicated the wage regressions based on the High School and Beyond Survey in Kane [1998] and the National Longitudinal Survey of Youth in Daniel, Black, and Smith [1997], we found that OLS estimates of the return to college selectivity based on the C&B survey were not significantly distinguishable from, though slightly higher than, those from these nationally representative data sets (see Dale and Krueger [1999]). In the next section we examine whether estimates of this type are confounded by unobserved student attributes.

TABLE II
MEANS AND STANDARD DEVIATIONS OF THE C&B DATA SET

	Unweighted		Weighted*			
	Full sample		Full sample		Matched applicants	
Variable	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Log(earnings)	11.121	0.757	11.096	0.747	11.148	0.737
Annual earnings (1995 dollars)	86,768	62,504	84,219	60,841	88,276	62,598
Female	0.391	0.488	0.392	0.488	0.385	0.487
Black	0.059	0.235	0.050	0.218	0.050	0.219
Hispanic	0.016	0.124	0.013	0.115	0.014	0.117
Asian	0.027	0.162	0.023	0.150	0.027	0.163
Other race	0.003	0.059	0.003	0.059	0.003	0.057
Predicted log (parental income)	9.999	0.354	9.984	0.353	9.997	0.349
Own SAT/100	11.820	1.661	11.672	1.634	11.875	1.632
School average SAT/100	11.949	0.928	11.655	0.943	11.812	0.943
Net tuition (1976 dollars)	2733	1077	2454	1145	2651	1094
Log(net tuition)	7.781	0.591	7.647	0.622	7.749	0.582
High school top 10 percent	0.427	0.495	0.418	0.493	0.427	0.495
High school rank missing	0.360	0.480	0.356	0.479	0.355	0.478
College athlete	0.100	0.300	0.078	0.268	0.085	0.279
Average SAT/100 of schools applied to	11.678	0.928	11.513	0.940	11.601	0.991
One additional application	0.222	0.416	0.225	0.417	0.490	0.500
Two additional applications	0.230	0.421	0.214	0.410	0.366	0.482
Three additional applications	0.176	0.380	0.156	0.363	0.134	0.340
Four additional applications	0.047	0.211	0.040	0.196	0.011	0.104
Undergraduate percentile rank in class	50.703	28.473	50.791	28.267	51.666	28.268
Attained advanced degree	0.565	0.496	0.542	0.498	0.573	0.495
Graduated from college	0.846	0.361	0.839	0.367	0.862	0.345
Public college	0.282	0.450	0.413	0.492	0.329	0.470
Private college	0.540	0.498	0.442	0.497	0.523	0.500
Liberal arts college	0.178	0.382	0.145	0.353	0.148	0.355
N	14,238		14,238		6,335	

* Means are weighted to make the sample representative of the population of students at the C&B institutions.

III. THE EFFECT OF COLLEGE SELECTIVITY AND OTHER CHARACTERISTICS ON EARNINGS

Table III presents our main set of log earnings regressions. We limit the sample to full-time, full-year workers, and estimate

TABLE III
LOG EARNINGS REGRESSIONS USING COLLEGE AND BEYOND SURVEY, SAMPLE OF MALE AND FEMALE FULL-TIME WORKERS

	Model					
	Basic model: no selection controls		Matched-applicant model	Alternative matched-applicant models		Self-revelation model
	Full sample	Restricted sample	Similar school-SAT matches*	Exact school-SAT matches**	*Barron's* matches***	
Variable	1	2	3	4	5	6
School-average SAT score/100	0.076	0.082	−0.016	−0.106	0.004	−0.001
	(0.016)	(0.014)	(0.022)	(0.036)	(0.016)	(0.018)
Predicted log(parental income)	0.187	0.190	0.163	0.232	0.154	0.161
	(0.024)	(0.033)	(0.033)	(0.079)	(0.028)	(0.025)
Own SAT score/100	0.018	0.006	−0.011	0.003	−0.005	0.009
	(0.006)	(0.007)	(0.007)	(0.014)	(0.005)	(0.006)
Female	−0.403	−0.410	−0.395	−0.476	−0.400	−0.396
	(0.015)	(0.018)	(0.024)	(0.049)	(0.017)	(0.014)
Black	−0.023	−0.026	−0.057	−0.028	−0.057	−0.034
	(0.035)	(0.053)	(0.053)	(0.049)	(0.039)	(0.035)
Hispanic	0.015	0.070	0.020	−0.248	0.036	0.007
	(0.052)	(0.076)	(0.099)	(0.206)	(0.066)	(0.053)
Asian	0.173	0.245	0.241	0.368	0.163	0.155
	(0.036)	(0.054)	(0.064)	(0.141)	(0.049)	(0.037)
Other/missing race	−0.188	−0.048	0.060	−0.072	−0.050	−0.192
	(0.119)	(0.143)	(0.180)	(0.083)	(0.134)	(0.116)
High school top 10 percent	0.061	0.091	0.079	0.091	0.079	0.063
	(0.018)	(0.022)	(0.026)	(0.032)	(0.024)	(0.019)
High school rank missing	0.001	0.040	0.016	0.029	0.025	−0.009
	(0.024)	(0.026)	(0.038)	(0.066)	(0.027)	(0.022)
Athlete	0.102	0.088	0.104	0.169	0.093	0.094
	(0.025)	(0.030)	(0.039)	(0.096)	(0.033)	(0.024)
Average SAT score/100 of schools applied to						0.090
						(0.013)
One additional application						0.064
						(0.011)
Two additional applications						0.074
						(0.022)
Three additional applications						0.112
						(0.028)
Four additional applications						0.085
						(0.027)
Adjusted R^2	0.107	0.110	0.112	0.142	0.106	0.113
N	14,238	6,335	6,335	2,330	9,202	14,238

Each equation also includes a constant term. Standard errors are in parentheses and are robust to correlated errors among students who attended the same institution.

Equations are estimated by WLS and are weighted to make the sample representative of the population of students at the C&B institutions.

* Applicants are matched by the average SAT score (within 25 point intervals) of each school at which they were accepted or rejected. This model includes 1,232 dummy variables representing each set of matched applicants.

** Applicants are matched by the average SAT score of each school at which they were accepted or rejected. This model includes 654 dummy variables representing each set of matched applicants.

*** Applicants are matched by the *Barron's* category of each school at which they were accepted or rejected. This model includes 350 dummy variables representing each set of matched applicants.

separate Weighted Least Squares (WLS) regressions for a pooled sample of men and women.[12] The reported standard errors are robust to correlation in the errors among students who attended the same college. With the exception of a dummy variable indicating whether the student participated on a varsity athletic team, the explanatory variables are all determined prior to the time the student entered college. Most of the covariates are fairly standard, although an explanation of "predicted log parental income" is necessary. Parental income was missing for many individuals in the sample. Consequently, we predicted income by first regressing log parental income on mother's and father's education and occupation for the subset of students with available family income data, and then multiplied the coefficients from this regression by the values of these explanatory variables for every student in the sample to derive the regressor used in Table III.

The basic model, reported in the first column of Table III, is comparable to the models estimated in much of the previous literature in that no attempt is made to adjust for selective admissions beyond controlling for variables such as the student's own SAT score and high school rank. This model indicates that students who attended a school with a 100 point higher average SAT score earned about 7.6 percent higher earnings in 1995, holding constant their own SAT score, race, gender, parental income, athletic status, and high school rank.

Column 2 also presents results of the basic model, but restricts the sample to those who are included in the "matched-applicants" subsample. As mentioned earlier, we formed groups of matched applicants by treating schools with average SAT scores in the same 25 point range as equally selective. We were able to match only 6,335 students with at least one other student who applied to, and was accepted and rejected by, an equivalent set of institutions. As shown in column 2 of Table III, when we estimate the basic model using this subsample of matched applicants, we obtain results very similar to those from the full sample. When we include dummies indicating the sets of matched applicants in column 3, however, the effect of school-average SAT is slightly negative and statistically indistinguishable from zero. Although the standard error doubles when we look within

12. The sample of women was too small to draw precise estimates from, but the results were qualitatively similar. The results for men were also similar and more precisely estimated (see Dale and Krueger [1999]).

matched sets of students, we can reject an effect of around 3 percent higher earnings for a 100 point increase in the school-average SAT score; that is, we can reject an effect size that is at the low end of the range found in the previous literature.

Column 4 of Table III presents results from an alternative version of the matched-applicant model that uses *exact matches*—that is, students who applied to and were accepted or rejected by exactly the same schools. When we estimate a fixed effects model for the 2,330 students we could exactly match with other students, the relationship between school-average SAT score and earnings is negative and statistically significant. Thus, the cruder nature of the previous matches does not appear to be responsible for our results.

To increase the sample and improve the precision of the estimates, we also used the selectivity categories from the 1978 edition of *Barron's Guide* as an alternative way to match students. *Barron's* is a well-known and widely used measure of school selectivity. Specifically, we classified the schools students applied to according to the following *Barron's* ratings: (1) Most Competitive, (2) Highly Competitive, (3) Very Competitive, and (4) a composite category that included Competitive, Less Competitive, and Non-Competitive. Then we grouped students together who applied to and were accepted by a set of colleges that were equivalent in terms of the colleges' *Barron's* ratings. This generated a sample of 9,202 matched applicants. As shown in Column 5 of Table III, when we estimated a fixed effects model for this sample the coefficient on the school-average SAT score was 0.004, with a standard error of 0.016. In short, the effect of school-SAT score was not significantly greater than zero in any version of the matched-applicant model that we estimated.

Results of the "self-revelation" model are shown in column 6 of Table III. This model includes the average SAT score of the schools to which students applied and dummy variables indicating the number of schools to which students applied to control for selection bias. The effect of the school-average SAT score in these models is close to zero and more precisely estimated than in the matched-applicant models.[13] Because the self-revelation model is

13. Because the C&B earnings data are topcoded, we also estimated Tobit models. Results from these models were qualitatively similar to our WLS results. When we estimated a Tobit model without selection controls (similar to our basic model), the coefficient (standard error) on school SAT score was .083 (.008); the coefficient on school-SAT score falls to −.005 (.012) if we also control for the variables in our self-revelation model.

TABLE IV
THE EFFECT OF SCHOOL-AVERAGE SAT SCORE ON EARNINGS IN MODELS THAT USE ALTERNATIVE SELECTION CONTROLS, C&B SAMPLE OF MALE AND FEMALE FULL-TIME WORKERS

	Parameter estimates		
Type of selection control	School-average SAT score	Selection control	N
(1) None (basic model)	0.076 (0.016)	—	14,238
(2) Average SAT score/100 of schools applied to (self-revelation model)	−0.001 (0.018)	0.090 (0.013)	14,238
(3) Average SAT score/100 of schools accepted by	−0.001 (0.021)	0.084 (0.017)	14,238
(4) Highest SAT score/100 of schools accepted by	−0.007 (0.018)	0.091 (0.021)	14,238
(5) Highest SAT score/100 of all schools applied to	0.010 (0.015)	0.075 (0.013)	14,238
(6) Highest SAT score/100 of schools applied to but not attended	0.042 (0.013)	0.051 (0.006)	9,358
(7) Average SAT score/100 of schools rejected by	0.052 (0.015)	0.072 (0.012)	3,805
(8) Highest SAT score/100 of schools accepted by not attended	0.039 (0.014)	0.049 (0.010)	8,257

Each model also includes the same control variables as the self-revelation model shown in column 3 of Table III. Standard errors are in parentheses and are robust to correlated errors among students who attended the same institution.

Equations are estimated by WLS and are weighted to make the sample representative of the population of students at the C&B institutions.

The first data column presents the coefficient on the average SAT score at the school the student attended; the second data column presents the coefficient on the selection control described in the left margin of the table.

likely to undercorrect for omitted variable bias, the fact that the results of this model are so similar to the matched-applicant models is reassuring.

Table IV presents parameter estimates from models that are similar to the self-revelation model, but use alternative selection controls in place of the average SAT score of the schools to which the student applied.[14] For example, the third row reports esti-

14. Each of these models also includes dummy variables representing the number of colleges the student applied to, because the number of applications a student submits may reveal his unobserved ability. However, even if we exclude the application dummies from the self-revelation model, the return to college average SAT-score is not significantly different from zero; in this model, the coefficient (standard error) on school-SAT score is .017 (.017).

mates from a model that controls for the average SAT score of the schools at which the student was accepted. The results of this model are similar to those in the self-revelation model in row 2, in that the effect on earnings of the average SAT score of the school the student attended is indistinguishable from zero. We also obtain similar results when we control for the highest school-average SAT score among the colleges that accepted the student (row 4) or the highest school-average SAT score among the colleges to which the student applied (row 5). Moreover, we consistently find that the average SAT score of the schools the student applied to, but either was rejected by or chose not to attend, has a large effect on earnings. For example, results from the model in row 7 show that a 100 point increase in the highest school-average SAT score among the colleges at which the student was rejected is associated with a 7 percent increase in earnings. These results raise serious doubt about a causal interpretation of the effect of attending a school with a higher average SAT score in regressions that do not control for selection.[15]

It is possible that, among students with similar application patterns, those who attended more selective colleges are also more likely to enter occupations with higher nonpecuniary returns but lower salaries (such as academia). A systematic relationship between college choice and occupational choice could possibly explain why we do not find a financial return to school selectivity. To explore this hypothesis further, we added twenty dummy variables representing the students' occupation in 1995 to each of our models. The coefficient (and standard error) on school average-SAT score was a robust .065 (.012) in the basic model, but fell to −.016 (.023) in the matched-applicant model and .010 (.012) in the self-revelation model. Thus, in the selection-adjusted models, the effect of school selectivity is indistinguishable from zero even if we control for occupation. Similar results hold if we control for students' occupational aspirations at

15. Because the C&B survey asks students about their college application behavior retrospectively, it is possible that students who had higher earnings later on were more likely to remember applying to elite schools, and less apprehensive about reporting that they were rejected. This type of memory bias would cause the coefficient on the selection control to be biased upward and the coefficient on school SAT score to be biased downward. Unlike the C&B survey, the NLS-72 survey asks students about their college applications within a year of the students' senior year in high school. Thus, our NLS-72 estimates (see subsection III.C) should not suffer from retrospective memory bias.

the time they were freshmen, as opposed to their actual occupation twenty years later.

Another explanation for the lack of return to school selectivity is that students who attend more selective colleges tend to be ranked lower in their graduating class than they would have been if they had attended a less selective school because of greater competition, and this effect may not be taken into full account by the labor market. To explore this possibility, we used college GPA percentile rank as the dependent variable and estimated the models in Table III. In all these models, students who attended a college with a 100 point higher average SAT score tended to be ranked 5 to 8 percentile ranks lower in their class, other things being equal. The improvement in class rank among students who choose to attend a less selective college may partly explain why these students do not incur lower earnings. Employers and graduate schools may value their higher class rank by enough to offset any other effect of attending a less selective college on earnings. If we add class rank to the wage regressions in Table III, we find that students who graduate 7 percentile ranks higher in their class earn about 3 percent higher earnings, which may largely offset any advantage of attending an elite college on earnings.

A. *Student Matriculation*

A key assumption of our matched-applicants models is that the school students choose to attend from the set of colleges to which they were admitted is unrelated to X_2, their unobserved abilities. To explore the plausibility of this assumption, we tested whether students' observed characteristics predict whether they choose to attend the most selective college to which they were admitted for the set of students who were admitted to more than one college. Specifically, we regressed a binary variable indicating whether the student attended the most selective school to which he or she was admitted on several explanatory variables. As shown in column 1 of Table V, within matched-applicant groups, parental income and high school class rank were not related to attending the most selective school. Students with higher SAT scores, however, were significantly more likely to attend the most selective college to which they were admitted. Similar results hold for the self-revelation model in column 2. These results suggest that students' choice of college may, in part, be nonran-

TABLE V
LINEAR REGRESSIONS PREDICTING WHETHER STUDENT ATTENDED MOST SELECTIVE COLLEGE FOR C&B SAMPLE OF STUDENTS ADMITTED TO MORE THAN ONE SCHOOL

	Parameter estimates	
	Matched-applicant model*	Self-revelation model
Predicted log (parental income)	−0.024	−0.037
	(0.026)	(0.030)
Own SAT score/100	0.020	0.021
	(0.005)	(0.007)
Female	0.034	0.033
	(0.014)	(0.028)
Black	0.056	−0.005
	(0.026)	(0.037)
Hispanic	−0.019	0.042
	(0.064)	(0.074)
Asian	0.019	0.074
	(0.026)	(0.050)
Other/missing race	−0.095	0.010
	(0.093)	(0.081)
High school top 10 percent	−0.014	−0.020
	(0.021)	(0.028)
High school rank missing	−0.035	−0.040
	(0.036)	(0.058)
Athlete	0.056	0.059
	(0.023)	(0.045)
Average SAT score/100 of schools applied to		−0.122
		(0.040)
One additional application		0.149
		(0.037)
Two additional applications		0.076
		(0.033)
Three additional applications		0.020
		(0.038)
N	5536	8257

Only students who were accepted by more than one school are included in the sample.

Each equation also includes a constant term. Standard errors are in parentheses, and are robust to correlated errors among students who attended the same institution.

Equations are estimated by WLS; weights are designed to make the sample representative of the population of students at the C&B institutions.

* Applicants are matched by the average SAT score (within 25 point intervals) of each school at which they were accepted and rejected. Model includes 1,079 dummy variables indicating each set of matched applicants.

dom, as students with higher values of an observed measure of ability choose to attend more selective schools. If students with higher values of unobserved ability also choose to attend more selective schools, then our estimates of the return to school quality will be biased upward. It is possible, however, that the sorting on unobserved abilities is in a different direction.

As mentioned, results of the self-revelation model are less likely to be contaminated by nonrandom student matriculation decisions: among students who applied to the same array of colleges, many attended less selective colleges not because they chose to, but because they were rejected by more selective colleges. By comparing students who were accepted to more selective colleges with those who were rejected by them, the self-revelation model is likely to undercontrol for unobserved student characteristics; therefore, our already-negligible estimate of the return to school-average SAT score is likely to be biased upward.

B. *Likely Effects of Measurement Error*

As is well-known, attenuation bias due to classical measurement error in an explanatory variable is exacerbated in fixed effects models (e.g., Griliches [1986]). Average SAT scores for some colleges as recorded in the HERI data are measured with error, since the data are self-reported by colleges, and colleges have an incentive to misrepresent their data. The correlation (weighted by number of students) between the school-average SAT score as measured by HERI data and the school average calculated from the students in the C&B database for 30 schools is .95. This correlation provides a rough estimate of the reliability of the SAT data, which we denote λ.

As a benchmark, it is useful to consider the likely attenuation bias in the school SAT coefficient in the OLS regression in column 1 of Table III. The additional attenuation bias in the matched-applicant and self-revelation models relative to the OLS model is relevant here. If the school-average SAT score is the only variable measured with error, and the errors are white noise, the proportional attenuation bias in the school-average SAT coefficient for a large sample is given by $\lambda' = (\lambda - R^2)/(1 - R^2)$, where R^2 is the coefficient of determination from a regression of the school SAT score on the other variables in the regression equation. In the OLS model in column 1, the attenuation bias is estimated to equal 5 percent. Relative to the OLS model, the estimated attenuation bias is 31 percent in the matched-applicant model and 8 percent in the self-revelation model.[16] Although the attenuation bias is nontrivial, even with this amount of measurement error it is likely that sizable effects would be detected. Moreover, one would not expect attenuation bias to cause the estimate to become negative, as was found in Table III.

Measurement error in the school-average SAT score would also generate measurement error in the matched-applicant dummies because they were both constructed from the HERI data. If we use the College and Beyond database to calculate the average SAT score of the school a student attended, and use the HERI data to group matched applicants, the estimated effect of the school-average SAT score is even more negative.

Probably a more important issue is whether the school-average SAT score is an adequate measure of school selectivity. We have focused on this measure because it is a widely used indicator of school selectivity in past studies. Moreover, college guidebooks prominently feature this measure of school selectivity. One justification for using the school-average SAT score is that it is related to the average quality of the potential peer group at the school. Nevertheless, it may be a poor proxy of school quality. For this reason, we also examined the effect of *Barron's* college ratings. Given the similarity of the results for the two measures, and the contrast between our results and the previous literature which only partially adjusts for student characteristics, we think the findings for the school-average SAT score are of interest.

C. *Results for National Longitudinal Survey of the High School Class of 1972*

To explore the robustness of our results in a nationally representative data set, we analyzed data from the National Longitudinal Study of the High School Class of 1972 (NLS-72). We restrict the NLS-72 sample to those students who started at a four-year college or university in October of 1972, and we use 1985 annual earnings data from the fifth follow-up survey. In 1985 the NLS-72 respondents were about six years younger than the C&B respondents were in 1995 (typically 31 versus 37). In the first follow-up survey, the NLS-72 asked students questions about other schools to which they may have applied in a fashion

16. The R^2 from a regression of school SAT on the other variables in the model in the matched-applicant model is .86, and in the self-revelation model it is .64.

similar to the C&B survey.[17] The NLS-72 also contains detailed information about students' academic and family backgrounds, allowing us to construct most of the same variables used in Table III.[18] The NLS-72 survey did not, however, collect information on respondents' full-year work status in 1985. We include in the sample all NLS-72 respondents (regardless of how much they worked) whose annual earnings exceeded $5,000.

The means and standard deviations for the NLS-72 sample, as well as regression estimates, are reported in Table VI. Because the NLS-72 sample is relatively small (2127 workers), we could not estimate the matched-applicant model; however, we were able to estimate the basic regression model and self-revelation model. The basic model without application controls, in column 2, indicates that a 100 point increase in the school-average SAT score is associated with approximately 5.1 percent higher annual earnings. However, the self-revelation model reported in column 3 suggests that the effect of school-average SAT score is close to zero, although the standard error of .023 makes it difficult to draw a precise inference. The school SAT score estimates based on the comparable C&B sample are similar: the coefficient (standard error) on school-average SAT score was .074 (.014) in the basic model and −.006 (.015) in the self-revelation model using the C&B sample and imposing similar sample restrictions (in 1995 dollars). These results suggest that our findings in Table III are not unique to the schools covered by the C&B survey.

To further compare our results with the previous literature, we also estimated these same models using the *Barron's Guide* to construct our measure of school quality. Following Brewer, Eide, and Ehrenberg [1999], we classified schools into the following six categories: Top private; Middle Private; Bottom Private; Top Public; Middle Public; and Bottom Public, where the "Top" category includes schools with Barron's ratings of "Most Competitive" and "Highly Competitive," the "Middle" category includes those with "Very Competitive" and "Competitive" ratings, and the "Low"

17. Specifically, respondents were asked on the NLS-72 first follow-up survey (in 1973), "When you first applied, what was the name and address of the FIRST school or college of your choice? Were you accepted for admission at that school?" These questions were repeated for the respondents' second and third choice schools. We matched the responses to these questions to the HERI file to determine the average SAT score in 1973 of the schools that students applied to.

18. We have parental income data for most of the NLS-72 sample, allowing us to control for actual, rather than predicted, parental income. We do not include a dummy variable for athletes because NLS-72 does not identify varsity letter winners.

TABLE VI

MEANS, STANDARD DEVIATIONS, AND LOG EARNINGS REGRESSIONS FOR NLS-72 POOLED SAMPLE OF MALE AND FEMALE WORKERS

		Selectivity measure: school SAT score		Selectivity measure: *Barron's* ratings	
		Parameter estimates		Parameter estimates	
	Variable means [standard deviation]	Basic model: no selection controls	Self-revelation model	Basic model: no selection controls	Self-revelation model
Variable Name	1	2	3	4	5
School-average SAT score/100	9.943	0.051	0.013		
	[1.181]	(0.010)	(0.023)		
Attended top private school	0.046			0.151	−0.018
	[0.210]			(0.056)	(0.066)
Attended middle private school	0.210			0.023	−0.047
	[0.408]			(0.033)	(0.035)
Attended low private school	0.071			0.032	0.000
	[0.257]			(0.044)	(0.044)
Attended top public school	0.009			0.218	0.096
	[0.094]			(0.112)	(0.115)
Attended middle public school	0.432			0.044	−0.007
	[0.495]			(0.028)	(0.029)
Log(parental income)	9.455	0.081	0.074	0.093	0.075
	[0.615]	(0.018)	(0.018)	(0.018)	(0.018)
Own SAT score/100	9.755	0.022	0.020	0.029	0.021
	[2.057]	(0.006)	(0.006)	(0.006)	(0.006)
Female	0.398	−0.384	−0.384	−0.384	−0.383
	[0.489]	(0.022)	(0.022)	(0.022)	(0.022)
Black	0.060	0.065	0.053	0.049	0.057
	[0.238]	(0.047)	(0.047)	(0.047)	(0.048)
Hispanic	0.016	0.096	0.085	0.096	0.089
	[0.124]	(0.084)	(0.084)	(0.084)	(0.084)
Asian	0.010	−0.175	−0.167	−0.166	−0.170
	[0.099]	(0.103)	(0.103)	(0.103)	(0.103)
Other/missing race	0.023	−0.525	−0.503	−0.485	−0.484
	[0.151]	(0.069)	(0.069)	(0.070)	(0.070)
High school top 10 percent	0.201	0.055	0.063	0.055	0.060
	[0.401]	(0.029)	(0.030)	(0.030)	(0.030)
High school rank missing	0.193	0.039	0.040	0.026	0.036
	[0.394]	(0.027)	(0.027)	(0.028)	(0.028)
Average SAT score/100 of schools applied to	9.996		0.034		0.050
	[1.114]		(0.025)		(0.014)
One additional application	0.246		0.026		0.027
	[0.431]		(0.025)		(0.025)
Two additional applications	0.202		0.107		0.108
	[0.402]		(0.028)		(0.028)
Three additional applications	0.008		0.010		0.008
	[0.089]		(0.115)		(0.115)
					8.788
					(0.193)
Adjusted R^2	—	0.199	0.205	0.198	0.2048
N	2,127	2,127	2,127	2,127	2,127
P-value for joint significance of school-type dummies				0.06	0.59

Each equation also includes a constant term. Standard errors are in parentheses. Equations are estimated by WLS, using the fifth follow-up sample weight. Respondents earning over $5,000 in 1985 are included, regardless of full-time work status. The mean of the dependent variable is 10.087; the standard deviation is .525. The categories "Top private" and "Top public" include schools with a "Most Competitive" or "Highly Competitive" *Barron's* rating, "Middle private" and "Middle Public" include schools with a "Very Competitive" or "Competitive" *Barron's* rating, and "Low private" and "Low public" include schools with a "Less Competitive" or "Non-Competitive" rating. "Attended low public" is the omitted category.

category includes those with "Less Competitive" and "Non-Competitive" ratings. Similar to Brewer, Eide, and Ehrenberg, we find that there is a large return to attending a Top Private college relative to a Bottom Public college if we estimate our basic model. However, if we estimate the selection adjusted models, the return to attending a Top Private falls considerably. For example, the differential between the Top Private and Bottom Public schools, with standard errors in parentheses, was .151 (.056) in the basic model and −.018 (.066) in the self-revelation model (shown in columns 4 and 5 of Table VI). Likewise, while the *Barron's* dummies are jointly significant at the 10 percent level in the basic model (p = .06), they are insignificant in the self-revelation model (p = .59). Thus, our findings for the school-average SAT scores appear to be robust when other measures of school selectivity are used.

D. Interactions between School-Average SAT and Parental Income

Table VII reports another set of estimates of the three models using the C&B data set (basic, matched-applicant, and self-revelation model) augmented to include an interaction between school-average SAT and predicted log parental income. In all the models we estimated, the coefficient on the interaction between parental income and school-average SAT is negative, indicating a higher payoff to attending a more selective college for children from lower income households. The interaction term is statistically significant and generally has a sizable magnitude. For example, based on the self-revelation model in column 3 of Table VII, the gain from attending a college with a 200 point higher average SAT score for a family whose predicted log income is in the bottom decile is 8 percent, versus virtually nil for a family with mean income.

E. The Effect of Other College Characteristics on Earnings

Although the average SAT score of the school a student attends does not have a robust effect on earnings once selection on unobservables is taken into account, we do find that the school a student attends is systematically related to his or her subsequent earnings. In particular, if we include 30 unrestricted dummy variables indicating school of attendance instead of the average SAT score in the models in Table III, we reject the null hypothesis that schools are unrelated to earnings at the .01 level.

TABLE VII
LOG EARNINGS REGRESSION ALLOWING THE EFFECT OF SCHOOL-AVERAGE SAT TO VARY WITH PARENTAL INCOME, C&B SAMPLE OF MALE AND FEMALE FULL-TIME WORKERS

	Parameter estimates		
	Basic model: no selection controls	Matched-applicant model*	Self-revelation model
Variable	1	2	3
School-average SAT score/100	0.701	0.537	0.581
	(0.185)	(0.224)	(0.180)
Predicted log(parental income)	0.915	0.819	0.839
	(0.212)	(0.247)	(0.204)
Predicted log of parental income * school SAT score/100	−0.063	−0.056	−0.058
	(0.019)	(0.023)	(0.018)
Own SAT score/100	0.018	−0.011	0.009
	(0.006)	(0.007)	(0.006)
High school top 10 percent	0.062	0.080	0.064
	(0.019)	(0.026)	(0.020)
High school rank missing	0.005	0.018	−0.005
	(0.024)	(0.038)	(0.022)
Athlete	0.104	0.105	0.095
	(0.025)	(0.040)	(0.025)
Average SAT Score/100 of schools applied to			0.089
			(0.013)
One additional application			0.062
			(0.011)
Two additional applications			0.073
			(0.021)
Three additional applications			0.110
			(0.028)
Four additional applications			0.085
			(0.027)
Adjusted R^2	0.108	0.112	0.114
N	14,238	6,335	14,238
Tab:			
Effect of a 200 point increase in school average SAT score for a person with predicted parental income:			
in the bottom 10 percent of the C&B sample	0.24	0.041	0.081
at the 50th percentile of the C&B sample	0.144	−0.045	−0.008
in the top 10 percent of the C&B sample	0.098	−0.085	−0.051

Each equation includes dummy variables indicating female, black, Hispanic, Asian, and other race and also includes a constant term. Standard errors are in parentheses and are robust to correlated errors among students who attended the same institution.

Equations are estimated by WLS and are weighted to make the sample representative of the population of students at the C&B institutions.

* Applicants are matched by the average SAT score (within 25 point intervals) of each school at which they were accepted or rejected. This model includes 1,232 dummy variables representing each set of matched applicants.

Thus, something about schools appears to influence earnings. A possible reason for the insignificance of school-average SAT in the selection-adjusted models is that the average SAT score is a crude measure of the quality of one's peer group. Since, to some extent, all schools enroll a heterogeneous group of students, it is possible for students to seek out the type of peer group they desire if they had attended any of the schools that admitted them. An able student who attends a lower tier school can find able students to study with, and, alas, a weak student who attends an elite school can find other weak students to *not study* with. What characteristics of schools matter, if not selectivity?

Table VIII presents models in which the logarithm of college tuition costs net of average student aid is the school quality indicator.[19] These models indicate that students who attend higher tuition schools earn more after entering the labor market. Notice also that the coefficient on the interaction term for parental income and tuition (shown in columns 2, 4, and 6) is negative, indicating that there is a higher payoff to attending a more expensive school for children from low-income families. The magnitude of the coefficient on tuition falls in the models that adjust for school selection, but remains sizable.[20] For example, the coefficient of .058 in column 5 implies an internal real rate of return of approximately 15 percent for a person who begins work after attending college for four years, then earns mean 1995 income throughout his career, and retires 44 years later.[21] The coefficient in column 3 implies an internal real rate of return of 13 percent. A caveat to this result, however, is that students who attend higher cost schools may have higher family wealth (despite our attempt to control for family income), so tuition may in part pick up the effect of family background on earnings.

Although the implied internal rates of return to investing in a more expensive college in Table VIII are high, one should

19. Net tuition for 1970 and 1980 was calculated by subtracting the average aid awarded to undergraduates from the sticker price tuition, as reported in the eleventh and twelfth editions of *American Universities and Colleges*. Then the 1976 net tuition was interpolated from the 1970 and 1980 net tuition, assuming an exponential rate of growth.

20. If we control for both net tuition and school SAT score in the same regression, the effect of net tuition is even larger. For example, the coefficient (standard error) on tuition from the matched-applicant model is .096 (.017); however, the coefficient on school SAT score from this model is negative and significant.

21. This rate of return would fall to 13 percent if we assumed that the person spent 1.5 years in graduate school (the average time spent in graduate school for the C&B sample) immediately after college.

TABLE VIII
LOG EARNINGS REGRESSIONS USING NET TUITION AS SCHOOL QUALITY INDICATOR, C&B MALE AND FEMALE FULL-TIME WORKERS

	Parameter estimates					
	Basic models: no selection controls		Matched-applicant models*		Self-revelation models	
Variable	1	2	3	4	5	6
Log(net tuition)	0.125	0.711	0.052	0.877	0.058	0.727
	(0.021)	(0.288)	(0.022)	(0.390)	(0.018)	(0.283)
Predicted log(parental income)	0.175	0.626	0.159	0.800	0.156	0.671
	(0.024)	(0.215)	(0.032)	(0.300)	(0.024)	(0.219)
Log(net tuition) * predicted log (parental income)		−0.059		−0.083		−0.067
		(0.029)		(0.040)		(0.029)
Own SAT score/100	0.022	0.022	−0.012	−0.012	0.009	0.008
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Female	−0.396	−0.395	−0.396	−0.395	−0.396	−0.395
	(0.012)	(0.012)	(0.024)	(0.023)	(0.013)	(0.013)
Black	−0.005	−0.005	−0.060	−0.062	−0.039	−0.040
	(0.031)	(0.031)	(0.052)	(0.052)	(0.034)	(0.035)
Hispanic	0.017	0.011	0.012	0.007	−0.006	−0.013
	(0.050)	(0.050)	(0.100)	(0.101)	(0.052)	(0.053)
Asian	0.178	0.176	0.237	0.236	0.152	0.149
	(0.033)	(0.033)	(0.064)	(0.064)	(0.036)	(0.036)
Other/missing race	−0.171	−0.171	0.067	0.058	−0.188	−0.188
	(0.120)	(0.120)	(0.180)	(0.179)	(0.117)	(0.117)
High school top 10 percent	0.073	0.074	0.083	0.084	0.067	0.067
	(0.021)	(0.021)	(0.026)	(0.026)	(0.021)	(0.021)
High school rank missing	0.008	0.009	0.020	0.022	−0.006	−0.004
	(0.023)	(0.023)	(0.039)	(0.039)	(0.022)	(0.022)
Athlete	0.106	0.107	0.102	0.101	0.090	0.091
	(0.027)	(0.027)	(0.040)	(0.040)	(0.024)	(0.024)
Average SAT score/100 of schools applied to					0.067	0.068
					(0.012)	(0.012)
One additional application					0.052	0.051
					(0.009)	(0.009)
Two additional applications					0.057	0.057
					(0.019)	(0.018)
Three additional applications					0.095	0.095
					(0.024)	(0.024)
Four additional applications					0.071	0.072
					(0.027)	(0.027)
Adjusted R^2	0.110	0.110	0.112	0.112	0.115	0.115
N	14,238	14,238	6,335	6,335	14,238	14,238

Each equation also includes a constant term. Standard errors are in parentheses, and are robust to correlated errors among students who attended the same institution.

Equations are estimated by WLS, and are weighted to make the sample representative of the population of students at the C&B institutions. Net tuition is average tuition minus average aid (see text).

* Applicants are matched by the average SAT score (within 25 point intervals) of each school at which they were accepted or rejected. This model includes 1,232 dummy variables representing each set of matched applicants.

recognize that the average cost of tuition has roughly doubled in real terms since the late 1970s, and the payoff to education increased in general since the late 1970s. The implicit internal real rate of return for the estimate in column 5 of Table VIII falls to 8 percent if tuition costs are doubled. Indeed, the supernormal return to investing in high-tuition education in the 1970s may explain why it was possible for colleges to raise tuition so much in the 1980s and 1990s.

College tuition may have a significant effect on subsequent earnings because schools with higher tuition provide their students with more, or higher quality, resources. We next summarize estimates of the effect of expenditures per student on subsequent earnings. Interestingly, the correlation between tuition and total expenditures per student in our sample of schools is less than .30, so differences in tuition result from factors in addition to spending per student, such as the value of the school's endowment and public support. One should also recognize limitations of our measures of expenditures per students: (1) undergraduate and graduate student expenditures are combined; (2) there are inherent difficulties classifying instructional and noninstructional spending; and (3) expenditures are lumpy over time.

To directly explore the effect of school spending, we included either the log of total expenditures per student (undergraduate and graduate), or the log of instructional expenditures per student, in place of tuition in the earnings equation.[22] Both measures of expenditures per pupil had a statistically significant and large impact on earnings in the basic model. When we estimated the matched-applicant model and the self-revelation model, the effect of expenditures per pupil was smaller and less precisely estimated. Although the effect of expenditures per pupil was statistically insignificant, the coefficient was positive in all but one of the models and implied substantial internal rates of return to school spending, similar in magnitude to those for tuition.[23] These results provide mixed evidence on the effect of expenditures per student on students' subsequent income, perhaps because spending per student is poorly measured.

22. We use 1976 expenditure data from the Integrated Postsecondary Education Data System (IPEDS) Survey.

23. The coefficient (and standard error) on log instructional expenditures per student if this variable was included instead of tuition in column 1, 3, and 5 of Table VIII were .114 (.057); .086 (.084); and .024 (.057). The corresponding coefficients for log total expenditures per student were .102 (.067); −.004 (.077); and .008 (.067).

IV. Conclusion

The colleges that students attend are affected by selection on the part of the schools that students apply to, and by selection on the part of the students and their families from the menu of feasible options. A major concern with past estimates of the payoff to attending an elite college is that more selective schools tend to accept students with higher earnings capacity. This paper adjusts for selection on the part of schools by comparing earnings and other outcomes among students who applied to, and were accepted and rejected by, a comparable set of institutions. Although our selection correction has many desirable features, a complete analysis of school selection also would model students' choice of colleges. Nonetheless, since college admission decisions are made by professional administrators who have much more information at their disposal than researchers who later analyze student outcomes, we suspect that our selection correction addresses a major cause of bias in past wage equations.

After we adjust for students' unobserved characteristics, our findings lead us to question the view that school selectivity, as measured by the average SAT score of the freshmen who attend a college, is an important determinant of students' subsequent incomes. Students who attended more selective colleges do not earn more than other students who were accepted and rejected by comparable schools but attended less selective colleges. Additional evidence of omitted variable bias due to the college application and admissions process comes from the fact that the average SAT score of schools that a student applied to but was rejected from has a stronger effect on the student's subsequent earnings than the average SAT score of the school the student actually attended. Furthermore, we find that students with higher SAT scores are more likely to attend the most selective college from their set of options, suggesting that students who attend the more selective schools may have higher unobserved ability. These results are consistent with the conclusion of Hunt's [1963, p. 56] seminal research: "The C student from Princeton earns more than the A student from Podunk not mainly because he has the prestige of a Princeton degree, but merely because he is abler. The golden touch is possessed not by the Ivy League College, but by its students."

It is possible, however, that attending a highly selective school helps some students and hurts others. If this were the case, and students were aware of it, then the students who chose to attend a less selective school even though they were admitted to a more selective one might be the students with attributes that lead them to benefit more from attending a less selective school. If this type of matching is important, then it is important for families to consider the *fit* between the particular attributes of their children and the school they attend. Moreover, if matching between the student's matriculation decisions and the potential payoff for that student from attending a particular (selective) college does take place, our estimates should not be interpreted as causal. But our results would still suggest that there is not a "one-size-fits-all" ranking of schools, in which students are always better off in terms of their expected future earnings by attending the most selective school that admits them.

This sentiment was expressed clearly by Stephen R. Lewis, Jr., president of Carleton College, who responded to the *U.S. News & World Report* college rankings (which ranked his school sixth among liberal arts colleges) by saying, "The question should not be, what are the best colleges? The real question should be, best for whom?"[24]

We do find that students who attend colleges with higher average tuition costs tend to earn higher income years later, after adjusting for student characteristics. This finding is not surprising given that one would expect students to receive a pecuniary or nonpecuniary benefit from higher tuition costs. Moreover, our findings for expenditures per student closely match those for tuition, although the effect of expenditures is less precisely measured. Because tuition and expenditures per student are positively correlated, these results suggest that tuition matters because higher cost schools devote more resources to student instruction. The internal real rate of return on college tuition for students who attended college in the late 1970s was high, in the neighborhood of 13 to 15 percent. But college tuition costs have risen considerably since the 1970s, driving the internal rate of return to a more normal level.

Finally, we find that the returns to school characteristics such as average SAT score or tuition are greatest for students from more

24. Quoted in Alex Kuczynski, " 'Best' List For Colleges By *U. S. News* Is Under Fire," *The New York Times,* August 20, 2001, p. C1.

disadvantaged backgrounds. School admissions and financial aid policies that have as a goal attracting qualified students from more disadvantaged family backgrounds may raise national income, as these students appear to benefit most from attending a more elite college. Ellwood and Kane's [1998] recent finding that college enrollment hardly increased for children from low-income families in the 1980s is troubling in this regard.

APPENDIX 1: SCHOOL-AVERAGE SAT SCORE AND NET TUITION OF C&B INSTITUTIONS

Institution	School-average SAT score in 1978	1976 Net tuition ($)
Barnard College	1210	3530
Bryn Mawr College	1370	3171
Columbia University	1330	3591
Denison University	1020	3254
Duke University	1226	3052
Emory University	1150	3237
Georgetown University	1225	3304
Hamilton College	1246	3529
Kenyon College	1155	3329
Miami University (Ohio)	1073	1304
Northwestern University	1240	3676
Oberlin College	1227	3441
Pennsylvania State University	1038	1062
Princeton University	1308	3613
Rice University	1316	1753
Smith College	1210	3539
Stanford University	1270	3658
Swarthmore College	1340	3122
Tufts University	1200	3853
Tulane University	1080	3269
University of Michigan (Ann Arbor)	1110	1517
University of North Carolina (Chapel Hill)	1080	541
University of Notre Dame	1200	3216
University of Pennsylvania	1280	3266
Vanderbilt University	1162	3155
Washington University	1180	3245
Wellesley College	1220	3312
Wesleyan University	1260	3368
Williams College	1255	3541
Yale University	1360	3744

The school-average SAT scores were obtained from HERI, and pertain to freshmen. Net tuition for 1970 and 1980 was calculated by subtracting the average aid awarded to undergraduates from the sticker price tuition, as reported in the eleventh and twelfth editions of *American Universities and Colleges*. The 1976 net tuition was interpolated from the 1970 and 1980 net tuition, assuming an exponential rate of growth.

MATHEMATICA POLICY RESEARCH, INC
PRINCETON UNIVERSITY

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