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CALIFORNIA AND THE SAT: A REANALYSIS OF UNIVERSITY OF CALIFORNIA ADMISSIONS DATA*

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Rebecca Zwick

Professor, Department of Education
University of California, Santa Barbara

Terran Brown

University of California, Santa Barbara

Jeffrey C. Sklar

University of California, Santa Barbara

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ABSTRACT

As part of the University of California's recent reconsideration of the role of the SAT in admissions, the UC Office of the President published an extensive report, *UC and the SAT* (2001), which examined the value of SAT I: Reasoning Test scores, SAT II: Subject Test scores, and high school grades in predicting the grade-point averages of UC freshmen (UCGPA), as well as the role of economic factors in predicting UCGPA. The analyses in *UC and the SAT* were based primarily on data that had been aggregated across freshmen cohorts (1996 through 1999) and across UC campuses. In the current study, by contrast, data were analyzed *within* campuses and cohorts and *then* summarized. While some of our conclusions are similar to those in *UC and the SAT*, others are not. Like the earlier study, for example, our reanalyses showed that, considered collectively, the SAT II tests required by UC (Writing, Math, and a third test of the applicant's choice) are slightly superior to the SAT I as a predictor of UCGPA. But our reanalyses also revealed considerable variability across campuses and freshman cohorts in the predictive value of high school grades and test scores, which was masked in the earlier analyses. Also, our reanalyses did not support the conclusion in *UC and the SAT* that SAT II scores are "less sensitive" to socioeconomic factors than SAT I

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scores, an assertion that was often repeated during the SAT debate that took place in 2001 and 2002.

1. BACKGROUND

In February, 2001, Richard Atkinson, then the President of the University of California, made a surprise speech advocating the elimination of the SAT I: Reasoning Test as a criterion for admission to UC (Atkinson, 2001; see also Atkinson, 2004). The idea of abandoning the SAT at the University of California had been hotly debated several years earlier but had faded from public awareness. Atkinson's speech, in which he advocated an immediate switch to college admissions tests that are tied closely to the high school curriculum, sparked a wholesale reconsideration of the University's admissions criteria.

Under UC policy, applicants must take either the SAT I: Reasoning Test or the ACT, as well as the SAT II Writing test, the SAT II Math test,¹ and a third SAT II test of their own choice. As part of the process of reexamining UC admissions policy, the Board on Admissions and Relations with Schools (BOARS), a University-wide faculty committee, commissioned an analysis of UC admissions data, to be carried out by researchers at the UC Office of the President (see Perry, Sawrey, & Brown, 2004). The result was an October 2001 report, *UC and the SAT: Predictive Validity and Differential Impact of the SAT I and SAT II at the University of California*, by Saul Geiser with Roger Studley. The study examined the value of SAT I: Reasoning Test scores, SAT II: Subject Test scores, and high school grades in predicting freshman grade-point average at the University of California (UCGPA) and also investigated the role of economic factors in predicting UCGPA.

Two of the main conclusions of the study conducted by the UC Office of the President (UCOP) were the following:

1. If the purpose of admissions tests is to predict freshman grades, "then the SAT II is unquestionably superior to the SAT I ... according to the UC data" (page 7).
2. "...SAT II achievement tests are not only a better predictor, but also a fairer test for use in college admissions insofar as they are demonstrably less sensitive than the SAT I to differences in socioeconomic and other background factors" (page 10).²

This study served a key role in discussions of California higher education policy: It was invoked to support President Atkinson's contention that the SAT I should be abandoned. The results of the research were studied intensively during the year following Atkinson's

¹ There are actually two SAT II Math tests: Level I C, which is the usual test, and Level II C, a more advanced test taken by fewer students. The data set used in the current study did not indicate which of the two tests was taken.

² A later version of this report (Geiser & Studley, 2002; reprinted as Geiser & Studley, 2004) contained slight revisions of these conclusions. The first conclusion was rephrased to say that "the SAT II achievement tests are consistently better predictors of student success at UC than the SAT I, although the incremental gain in prediction is relatively modest and there is substantial redundancy across the tests." The second conclusion was restated to say that "the predictive validity of the SAT II appears to be less conditioned by socioeconomic factors than is the SAT I" (Geiser & Studley, 2004, p. 125).

speech, as UC officials met regularly with the College Board. In early 2002, the College Board announced that it planned to alter the SAT I; the proposed changes were approved by the College Board Trustees in June 2002. The new SAT, scheduled to be in place by 2005, will substitute short reading items for the controversial verbal analogy items, incorporate more advanced math content, and add a writing section that contains both multiple-choice questions and an essay. These changes are expected to better align the test with the college preparatory courses UC applicants are required to take.

2. GOALS OF THE CURRENT ANALYSES

UC and the SAT provided invaluable information on the interrelationships among grades, test scores, and socioeconomic background for UC students. As explained in Sections 2.1 - 2.2, however, the conclusions that can be drawn from the analyses are limited because of the degree to which data were aggregated. Analyses that are more fine-grained can reveal further information about these complex associations. In the present study, we sought to expand upon the UCOP study in two ways, outlined below.

2. 1. Goal 1: Analysis of Campus and Cohort Effects

Most of the UCOP analyses aggregated data over seven UC campuses, four freshman cohorts (1996 through 1999), or both (see Table 1A). Combining data from dissimilar groups of individuals can obscure relationships among variables or produce spurious evidence of such relationships. This phenomenon is known in statistical jargon as *confounding of within-group effects with between-group effects*. An example is the following: Suppose that there is *no correlation* between test scores and college grades at either Campus A or Campus B (i.e., no within-school effect). At Campus B, however, both grades and test scores tend to be higher than at Campus A—a between-school effect. If the data from the two schools are combined and the correlation recalculated, there will appear to be a correlation between test scores and grades, but the association will be due entirely to the fact that, at Campus B, both grades and test scores are higher than at Campus A. More subtle manifestations of this phenomenon can and do occur. (Howell, 1997, pp. 267-268, gives an example based on actual data.) That is why test validity studies are typically conducted *within* schools. Results can be aggregated later if desired (e.g., Ramist, Lewis, & McCamley-Jenkins, 1994; Zwick, 1991 and 1993); this kind of *pooled within-school analysis* does not lead to the confounding phenomenon.

Aggregating the data across *cohorts* may present particular problems. In a study of SAT validity sponsored by the UC Linguistic Minority Research Institute (Zwick & Schlemer, 2004), a decision was made to conduct separate analyses of 1997 and 1998 applicants to UCSB after systematic differences between the two cohorts became evident. In particular, the correlations between test scores and freshman GPA varied substantially across cohorts, and these differences were especially evident in analyses of ethnic and language groups. This lack of consistency was probably due in part to the fact that the cohorts differed widely in the amount of missing data for language and ethnicity. In 1997, ethnicity information was unavailable for 1.1% of freshmen, and language information was unavailable for 2.4%. In 1998, these percentages jumped to 14.5% and 44.1%, respectively. A seemingly plausible explanation for these large differences is the fact that the 1998 entrants were the first cohort affected by California's Proposition 209, which eliminated affirmative action in admissions to public institutions. Cohort effects can be expected in the data used for *UC and the SAT* for similar reasons.

The analyses of the prediction of freshman GPA for individual ethnic groups in *UC and the SAT* were also based on data that had been aggregated across cohorts and campuses. The test validity literature suggests that campus-level analyses that focus on ethnic groups can reveal important differences among these groups. For example, among 1998 freshmen at UCSB (Zwick & Schlemmer, 2004), high school GPA predicted freshman GPA better than SAT I scores in most student groups, as is typical, but SAT I Verbal score was the best predictor for both Asian-Americans and Latinos who said English was not their best language. (SAT II scores were not considered.) Useful information can be obtained from the UCOP data by conducting further analyses of the degree to which prediction patterns vary across ethnic groups, within campuses and cohorts.

2.2. Goal 2: Analysis of Scores on Individual Tests Instead of Test Score Composites
In most of the UCOP analyses, "SAT I score" was a composite of SAT I Verbal and Math scores; "SAT II score" was a composite of SAT II Writing and Math scores and the score on the third SAT II test selected by the applicant. The SAT II composite is of particular concern because it does not have a consistent meaning for all applicants. The identity of the third SAT II test can make a substantial difference in the "behavior" of the SAT II composite. For example, research by the College Board and by UCOP suggests that SAT II language test scores behave quite differently from other SAT II scores (Bridgeman, Burton, & Cline, 2004; Geiser & Studley, 2001, October, pp. 14-15).

To see how forming composite scores can obscure important information, consider a simple example from the most recent national data on college-bound seniors (College Board, 2003). The average SAT I composite score (as defined by UCOP) was slightly higher for Asian-Americans (1083) than for Whites (1063). By considering the SAT I test sections separately, however, we can see that Asian-Americans, who are much more likely to have taken precalculus and calculus than Whites, actually scored an average of 41 points *higher* than Whites on the Math section and 21 points *lower* on the Verbal section.

It is also important to note that the use of composites does not yield the same validity coefficients (in this case, correlations with freshman GPA) that would result if each component test were considered separately. For example, the correlation of the SAT I composite with freshman GPA is not, in general, the same as the multiple correlation that would be obtained if SAT I Verbal and Math scores were considered as two separate predictors of freshman GPA in a regression equation. The differences can be substantial.³ In general, much more can be learned about the distinctions between the SAT I and the SAT II if each component score is examined individually.

3. DATA

The analyses conducted in the current study were based on two data sets supplied by the UC Office of the President in response to a formal request. The primary data set,

³ Both kinds of validity coefficients can be obtained theoretically, given certain assumptions about correlations and variances. I constructed an example in which SAT I Math and Verbal scores had the same variance and had an intercorrelation of .7. Math score and Verbal score were correlated .2 and .4, respectively, with freshman GPA. All these assumptions are plausible. In this example, the correlation of the SAT I composite with freshman GPA is .325, while the multiple correlation obtained from the regression of GPA on SAT I Verbal and Math scores (considered as two predictors) is .415.

which corresponds to the one used in *UC and the SAT*, contains information on 77,893 students admitted to seven campuses of the University of California (Berkeley, Davis, Los Angeles, Irvine, Riverside, San Diego, Santa Barbara) in 1996, 1997, 1998, and 1999. UC Santa Cruz was excluded from the data base because it does not assign conventional grades, and UC San Francisco was excluded because it is solely a graduate institution. Data for UC Riverside were missing for 1997 and 1998 (as described in *UC and the SAT*). The variables contained in the data set include high school grade-point average (HSGPA),⁴ freshman GPA at the University of California (UCGPA), admissions test scores, ethnicity, and, for 85 percent of the students (66,584 of 77,893), data on parental income and education. The admissions test scores consist of SAT I Verbal and Math scores, SAT II Math and Writing scores, and the score on the third SAT II test chosen by the applicant. The identity of the third test is not included in the data set, however.

The following additional data were requested from UCOP for use in the current project:

- Newly available data on UC Riverside students that were used by UCOP to prepare the January 2002 report, *Research Addendum: Additional Findings on UC and the SAT*, by Saul Geiser and Roger Studley.
- Data on students' gender, primary language, the identity of the "third" SAT II test submitted, and the multiple-choice and writing sample subscores of the SAT II.
- Data on applicants, as well as enrolled students.

The first of these requests was met, but the remaining ones were not. The Riverside data set that was supplied included data for all four cohorts (7,282 cases). Except where noted, this secondary data set was used as the source of Riverside data in the analyses reported here. The total number of cases analyzed in the current study (using the secondary data set for UC Riverside and the primary data set for the remaining six campuses) is 81,801. Table 1A shows the number of included students by campus and cohort; Table 1B gives the number of students for whom parental income and education data were available. Within the primary and secondary data sets, all records have complete data on high school grades, admissions test scores, and UCGPA.⁵

Table 1C gives the admission rates for the campus-cohort combinations involved in this study, which are useful in interpreting the analysis results. UC Berkeley and UCLA are the most selective of the seven campuses, UC Riverside is least selective, and the remaining campuses occupy a middle ground.

⁴ According to Geiser and Studley (2004, p. 127), "HSGPA used in this analysis is an honors-weighted GPA with additional grade-points for honors-level courses; HSGPA is uncapped and may exceed 4.0."

⁵ No information on the number of cases excluded by UCOP because of missing data on these variables was provided with the data set, nor does it appear in *UC and the SAT*. In response to an inquiry, UCOP analysts reported that they excluded 10,528 additional cases because of incomplete data on grades or test scores (R. Studley, personal communication, February 21, 2002). In our own study, 27 students in the secondary Riverside data set had to be excluded from analyses because their recorded UCGPAs were out of range; some were as high as 15. We later discovered that a total of six cases in the remaining 74,519 records in the UCOP data set (.008%) also had out-of-range UCGPAs. Because the number was small and the out-of-range UCGPAs were not extreme (ranging between 4.3 and 6.55), no analyses were redone.

4. ANALYSES

The analyses conducted for this project are summarized in the next three subsections. Section 4.1 presents descriptive information for key variables. Section 4.2 gives results on the prediction of UCGPA within each campus and cohort for several different regression models, some of which contain parental income and education along with test scores and high school grades. Section 4.3 describes analyses that focus on the relative accuracy of the prediction of UCGPA for African-American, Asian-American, Latino, and White students.

4.1. Descriptive Results for Key Variables

Tables 2A-2I give, for the four cohorts and seven campuses, the means and standard deviations of the key variables used in the study: high school GPA, SAT I Verbal score, SAT I Math score, SAT II Writing score, SAT II Math score, SAT II third test score, UCGPA, parent income, and parent education. Tables 2A-2G show that grades and test scores were typically highest at Berkeley and UCLA and lowest at Riverside. In general, the academic qualifications of students increased over time, particularly at UCSB. Parental income was extremely variable within each campus-cohort combination, but on average was highest at Santa Barbara and Berkeley (with mean income always exceeding \$80,000 per year) and lowest by far at Riverside (never exceeding \$57,000). Income (expressed here in constant 1998 dollars) increased over time at most campuses. The average number of years of parental education (for the student's more educated parent) exceeded 16 in all cohorts at Berkeley, UCSD, and UCSB. The average parental education was lowest at Riverside (14.6 years) and Irvine (15.5 years).

4.2. Prediction of UCGPA Within Campuses and Cohorts

To assure that we were working with exactly the same data set as Geiser and Studley, we first conducted analyses like those used to produce Tables 1, 2, and 3 of *UC and the SAT* (using the primary data set originally provided to us). Our results were identical to those reported. Following that, we estimated a number of alternative regression models for each campus and cohort. In each case, the dependent variable was UCGPA. The predictors included in each of our ten primary models are summarized in Table 3.

Table 4 gives the estimated squared correlations (R^2) for Models 1-8, which do not include parental income and education. The medians of the R^2 values for each model appear at the foot of the table. For Models 6, 7, and 8, the R^2 values are also plotted in Figures 1-3. A comparison of these models shows that the SAT II-HSGPA combination is slightly more effective in predicting UCGPA than is the SAT I-HSGPA combination (Model 6; $R^2 = .168$), explaining about one percent more of the variance in UCGPA when only the SAT II Math and Writing tests are included (Model 7; $R^2 = .179$), and two percent more when the third test is included as well (Model 8; $R^2 = .186$).

While these results corroborate the findings of *UC and the SAT* that SAT II scores are superior to SAT I scores as predictors of UCGPA, the differences in the proportion of explained variance are tiny. Also, as discussed below, the predictive power of the SAT II is largely attributable to the SAT II Writing test. Using SAT I scores alone (without HSGPA) to predict UCGPA produces an R^2 of only .084 (Model 2). The R^2 values for the remaining models range between .110 and .126. It is worth noting that the summary values of R^2 in Table 4, which are the medians of the within-campus-cohort results, are all smaller than the (roughly) corresponding values in *UC and the SAT* (Table 1, p. 3). For example, the R^2 for HSGPA reported in *UC and the SAT*, computed on the

combined data for all campuses and cohorts, is .154; the corresponding value in Table 4 of the current report is .126. The likely reason is the type of confounding of effects discussed in Section 2.1: The R^2 values computed on the combined data are inflated because campuses and cohorts with high values on the predictor variables also tend to have high freshman grades.⁶

Two other trends are evident in the results of Table 4 and Figures 1-3: First, the predictive value of each model varies considerably across campuses. For models 6-8, prediction tends to be weakest at UC San Diego and best at UC Davis. Second, there is a tendency for the R^2 values to decrease between 1996 and 1999, although this pattern is by no means consistent across the seven campuses. A possible reason for the variation in predictive effectiveness is that it results from differences in selectivity: UC San Diego is the third most selective school (after Berkeley and UCLA) and UC Davis is less selective (see Table 1C). In addition, admission rates generally fell between 1996 and 1999 (Table 1C). It would seem reasonable to expect the greater selectivity in some campuses and cohorts to reduce the variability of academic performance variables and hence the correlations among them. It must be noted however, that the standard deviations reported in Tables 2A-2G do not seem to support this hypothesis.

One of our analysis goals was to reexamine the effects of adding parental income⁷ and education to academic variables as predictors of UCGPA. The conclusion in *UC and the SAT* that “much of the apparent relationship between the SAT I and UC freshman grades is conditioned by socioeconomic factors” (p. 9) was based on a regression analysis performed on combined data for all cohorts and campuses. First, Geiser and Studley fit a regression model in which HSGPA and test scores were used to predict UCGPA. Then, they added two more predictors to the model: parental income and education. They found that “the predictive weights for both the SAT II and HSGPA are undiminished (and in fact increase slightly). In contrast, the weight for the SAT I ... falls sharply” (p. 9). The standardized regression coefficients in question are shown in Table 5, which is equivalent to Table 6 of the UCOP report (p. 8). (A more detailed version of this table appears as Table 7 of Geiser & Studley, 2004, p. 136.) We conducted analyses within campuses and cohorts, with each test component considered separately, to determine whether the pattern shown in Table 5 was evident. In fact, our results did not generally follow this pattern.

Tables 6 and 7 give the estimated standardized regression coefficients, as well as the R^2 values for Models 9 and 10, respectively. The last row gives the medians of the regression coefficients and R^2 values. Both models include high school GPA and all five test scores; Model 10 includes parental income and education as well. To facilitate comparison of the models, both were estimated using only those students for whom income and education data were available (see Table 1B).

A significant finding is that adding parental income and education increases the proportion of explained variance (R^2) by an average of only .006 (i.e., from .188 in Table 6 to .194 in Table 7). Furthermore, on average, the coefficients of the individual

⁶ The range restriction phenomenon described in Section 5.1 is also relevant.

⁷ The analyses in *UC and the SAT* used the log of parental income, and therefore we did so in all of our analyses as well. (Only the descriptive results in Table 2H are based on untransformed income. In economic analyses, the log transformation is commonly applied to income to make the distribution more symmetric.)

predictors changed by no more than .02. The average coefficients for the SAT I Verbal and SAT II Writing tests decreased trivially, while the average coefficient for HSGPA and for the SAT II third test increased trivially. For the remaining variables, the average coefficients stayed the same to two decimal places. These findings, then, are not consistent with the conclusion in *UC and the SAT* that the predictive power of the SAT I was more “sensitive” to socioeconomic factors than the predictive power of the SAT II. Adding parental income and education, in fact, had very little impact on the regression results, as reflected in the minimal changes in R^2 values within campuses and cohorts.⁸ There are several possible explanations for the difference between these conclusions and those of *UC and the SAT*. The most important is that, for reasons described earlier, the analyses in this study have been conducted within campus and cohort. Averaging the within-group analyses is a better way to assess the effectiveness of these variables in predicting UCGPA than is analyzing the combined data. Second, our analyses used each test score separately, rather than forming SAT I and SAT II composites. A third reason is that our analyses incorporated the updated data set from UC Riverside. The analyses of Tables 6 and 7 are therefore based on 70,610 cases (see Table 1B), while the related analyses in *UC and the SAT* were based on 66,584 cases.

Several other aspects of the results in Tables 6 and 7 are also noteworthy. First, the results show that, given the set of predictors considered here, high school grades are the single most effective predictor of UCGPA (i.e., its average standardized regression coefficient is highest), followed by the SAT II Writing Test. The SAT II third test also makes a contribution, although its effectiveness varies considerably across campuses and cohorts. The remaining test scores (SAT I Math and Verbal, SAT II Math) contribute little, given the predictors included in Models 9 and 10.

4.3 Prediction Accuracy for Ethnic Groups

An important goal of our investigation was to determine whether prediction of UCGPA was equally effective for all ethnic groups. One way we studied this was to combine the data for all ethnic groups, estimate a regression equation (to predict UCGPA from test scores and high school grades), and then examine the degree to which the use of this common equation produced predicted UCGPA values that tended to be too high (“overprediction”) or too low (“underprediction”) for each group. In actual applications of regression analysis in college admissions, a single equation is typically derived for all students. If this equation yielded UCGPA predictions that were systematically “off” for a particular group, this result would be consistent with the definition of test bias articulated by Anne Cleary. Her definition states that a test is biased against a particular subgroup of test-takers “if the criterion score [in this case, UCGPA] predicted from the common regression line is consistently too high or too low for members of the subgroup” (Cleary, 1968, p. 115). Researchers today would be more likely to use the term “prediction bias” rather than “test bias” because there are many possible reasons for errors in prediction. Because sample sizes for some ethnic groups were small, we conducted this analysis for two “mega-cohorts”: the 1996 and 1997 class, combined, and the 1998 and 1999 class, combined. (Recall that a major change in UC admissions policy—the elimination of affirmative action—went into effect beginning with the class of 1998.) We conducted the prediction accuracy analyses for African-American, Asian-American, Hispanic, and

⁸ In a study of 1993 graduates of public high schools who entered UC, Rothstein (2004) found that high-school-level socioeconomic variables did contribute substantially to the prediction of UCGPA. Data from all UC undergraduates (except those from Santa Cruz) were combined.

White students. The numbers of students in other ethnic groups, such as Native Americans, were too small to allow separate analysis.

Tables 8-14 show the results of the prediction accuracy analyses for Models 6 and 7 for the two mega-cohorts at each of the seven campuses. As shown in Table 4, Model 6 includes HSGPA and SAT I Verbal and Math scores; Model 7 includes HSGPA and SAT II Writing and Math scores. The main entries of Tables 8-14 give the difference, in grade-points, between the average observed and predicted UCGPA values (observed minus predicted) for each group in each analysis. It is a property of least squares regression that the sum of the prediction errors for all observations within a particular analysis will be zero, implying that underpredictions for some groups will be balanced by overpredictions for other groups. (The sum of the prediction errors shown in Tables 8-14 is not zero because the results for the "other" group have been omitted from the displays.) The results show that prediction errors are quite similar for the SAT I and SAT II models, which is consistent with the conclusion reported in *UC and the SAT* (p. 13). In 22 of 28 analyses (7 campuses x 2 mega-cohorts x 2 models), White students' UCGPAs were underpredicted by at least .05 (in grade-points), with one discrepancy reaching nearly .15 (UC Irvine, 1996-1997). Hispanic and Asian-American students were each overpredicted by an average of at least .05 in 12 of 28 analyses, and African-Americans were overpredicted by at least .05 in four analyses and underpredicted by at least .05 in four. Prediction errors over .05 were somewhat more likely to occur in 1997-1998 than in 1996-1997. Application of regression models that incorporated parental income and education (not shown) produced essentially the same pattern of prediction errors.

Studies have often found that GPAs were overpredicted for Black and Hispanic test-takers and underpredicted for White and Asian-American test-takers (see Young, 2004 for a review). There are a number of theories about the reasons for these pervasive patterns of prediction errors. Some have attributed the phenomenon to statistical artifacts; others believe they are related to the differing college experiences of various student groups. A brief overview of the most prevalent hypotheses appears here; see Zwick, 2002, pp. 117-124 for a more detailed review. One conjecture is that minority and White students are likely to differ in ways that are not fully captured by either their test scores or their high school grades. For example, a Black student and a White student who both have high school GPAs of 3.5, SAT Verbal scores of 600, and SAT Math scores of 650 may nevertheless differ in terms of factors like the quality of early schooling, the environment in the home, and the aspirations of the family, all of which can influence academic preparation.

A related explanation for overprediction (Vars & Bowen, 1998) is that among qualified applicants, a smaller percentage of Whites than Blacks are admitted to college. White college students, according to this reasoning, are therefore more likely to have been selected using stringent (though perhaps informal) criteria that involve academic factors not captured by SAT scores (or, presumably, high school grades). In a similar vein, Linn (1983) laid out an explicit statistical model that shows how affirmative action policies could explain the phenomenon. A more controversial theory about overprediction is that college grades are biased against Blacks and other people of color, and tests are not. Under this scenario, raised by Klitgaard (1985), tests give a more accurate reading of students' capabilities than the subsequent evaluations of their academic performance.

A technical explanation that has been offered repeatedly in the psychometric literature is that overprediction occurs because both SAT scores and high school grades are

imprecise measures of academic abilities. This unreliability can be shown to distort regression results in a way that produces overpredictions for lower-scoring groups and underpredictions for higher-scoring groups.⁹ Seemingly, then, the imprecision of test scores and grades could explain overprediction for Blacks and Hispanics, and underprediction for Asian-Americans and Whites. But one major research finding argues against this technical factor as an all-purpose explanation: Female SAT-takers tend to score lower than male SAT-takers, yet their later grades tend to be *underpredicted*. In addition, the high reliability of the SAT (typically between .91 and .94 per section; see College Board and ETS, 1998, p. 29) suggests that the effects of test score imprecision on the regression results are likely to be small.

Another category of hypotheses about overprediction is based on the assumption that when in college, minority students are not fulfilling their academic potential, which is assumed to be accurately captured by the tests. This "underperformance" could occur because of outright racism or because of a campus environment that is inhospitable to people of color, or it could be related to a greater occurrence among minority students of life difficulties, including financial problems, that interfere with academic performance. It has also been hypothesized that anxieties, low aspirations, or negative attitudes may interfere with the academic success of minority students. (e.g., see Bowen & Bok, 1998, p. 84; McWhorter, 2000).

The "stereotype threat" theory of Steele and Aronson (1998) has been offered as another possible explanation for overprediction (e.g., Vars & Bowen, 1998, p. 475; Bowen & Bok, 1998, p. 81). Stereotype threat—"the threat of being viewed through the lens of a negative stereotype, or the fear of doing something that would inadvertently confirm that stereotype"—produces stress, which causes students to "learn to care less about the situations ... that bring it about" and, ultimately, to perform more poorly (Steele, August 1999, pp. 4, 5). In some circumstances, the researchers claim, merely asking test-takers to state their sex or ethnic group can be damaging to their performance. Steele and Aronson (1998) focused on the impact of stereotype threat on African-American students in testing situations, and concluded by saying that their "analysis uncovers a social and psychological predicament that is rife in the standardized testing environment ..." The goal of their studies, they said, was to "seek to explain why blacks underperform in college relative to equally well-prepared whites" (Steele & Aronson, 1998, p. 425-426).

Although the stereotype threat research is intriguing, it does not provide a straightforward explanation of the overprediction/underperformance phenomenon. If stereotype threat depressed standardized test performance, but didn't affect subsequent academic work, it would be expected to lead to *underprediction* because the affected students would perform *better* in college than their (depressed) test scores would indicate. To explain the existing pattern of test results and college grades, we'd have to hypothesize that stereotype threat had *more* effect on college grades than on admissions test performance, which seems contrary to the researchers' implication that standardized testing situations are particularly evocative of stereotype threat (Steele & Aronson, 1998; Steele, 1997).

⁹ The effect is simplest to understand in the case of one predictor. Here, under typical assumptions about the nature of measurement errors in test scores, the effect of the measurement error on the regression analysis is to produce a regression line that is flatter (less steep) than the line that would theoretically be obtained with an error-free predictor (see Snedecor & Cochran, 1967, pp. 164-166).

For now, the perplexing overprediction phenomenon remains, at least in part, a mystery. Unmeasured differences between White students and Black and Hispanic students with the same test scores and previous grades certainly explain at least part of the overprediction. But it seems plausible that a greater incidence among minority students of life difficulties and financial problems in college contributes to the phenomenon as well.

The finding of overprediction for Asian-American students in the current study is somewhat unusual. A recent finding by Zwick and Schlemmer (2004) suggests that this result may be related to the language background of California students. In a study of two freshman cohorts (1997 and 1998) at UCSB, Zwick and Schlemmer found accurate prediction or underprediction of freshman GPA for Asian-American students who said that their first language was English, and some evidence of overprediction for those who said their first language was "another language." Overprediction was quite severe for a third group of Asian-Americans—those who said their first language was "English and another language." Aggregating the three groups in the Zwick and Schlemmer study (to maximize the comparability of the results with those of the current study) yields a finding of overprediction (.05 in 1997 and .06 in 1998) for a regression model containing HSGPA and SAT I Verbal and Math scores.

5. SUMMARY AND DISCUSSION

The current study shows that valuable information can be obscured when aggregated data are analyzed as in *UC and the SAT*. Our reanalyses of the UC admissions data revealed considerable variability across campuses and freshman cohorts in the predictive value of high school grades and test scores, which was masked in the analysis of the combined data. Also, our analyses within campuses and cohorts did not support the conclusion in *UC and the SAT* that SAT II scores are "less sensitive" to socioeconomic factors than SAT I scores, an assertion that was repeated countless times during the recent SAT debate in California. Our main findings were as follows:

a. *The SAT II is slightly superior to the SAT I as a predictor of UCGPA, although the pattern of results across campuses and cohorts is similar for the two tests.* For each campus and cohort, several alternative prediction models were compared. The combination of SAT II Math and Writing scores and HSGPA explained about one percent more of the variance in UCGPA than the combination of SAT I Verbal and Math scores and HSGPA. When the SAT II third test was included along with the Math and Writing tests, the superiority of the SAT II-HSGPA model over the SAT I-HSGPA model increased to two percent of the variance in UCGPA.

b. *Of the five test scores considered (two SAT I scores and three SAT II scores), the SAT II Writing test emerged as the best predictor of UCGPA in the analyses within campus and cohort.* *UC and the SAT* also reported on the effectiveness of the SAT II Writing Test as a predictor (e.g., p. 19). As in most such studies, our analyses showed that HSGPA was the best single predictor of UCGPA.

c. *The degree to which UCGPA could be predicted by admissions tests and high school grades varied substantially over campuses and cohorts. In general, predictive effectiveness declined between 1996 and 1999.* Although the results are not entirely

clear-cut, there is a tendency for predictive effectiveness to be smaller at the campuses with lower admission rates (Berkeley, UCLA, UCSD) than at the remaining campuses, and for predictive effectiveness to decrease between 1996 and 1999, during which time admission rates also tended to decrease. It would seem reasonable to expect the greater selectivity in some campuses and cohorts to reduce the variability of academic performance variables and hence the correlations among them. It must be noted however, that the standard deviations of test scores and grades for the students in this study do not seem to support this hypothesis. In general, all models in the current study appeared to be less effective in predicting UCGPA (i.e., produced smaller R^2 values) than the analogous models in *UC and the SAT*. This disparity suggests that the findings on the aggregated data were inflated by the confounding of two kinds of effects: (1) the relationship of the various predictors with UCGPA in terms of the *average values* for the 28 campus-cohort combinations (the “between” effect), and (2) the relationship of the various predictors with UCGPA for students within each of the campus-cohort combinations (the “within” effect).

d. *The predictive power of the SAT II was not found to be “less conditioned by socioeconomic factors” than the predictive validity of the SAT I.* In *UC and the SAT*, Geiser and Studley fit a regression model to the combined data in which HSGPA and test scores were used to predict UCGPA. When they subsequently added parental income and education to the model, they found the predictive weights for the SAT II and HSGPA to be undiminished, while the weight for the SAT I fell sharply (p. 9). This pattern of results led to the inference that “much of the apparent relationship between the SAT I and UC freshman grades is conditioned by socioeconomic factors” (p. 9). This, in turn, led to a conclusion that the SAT II was more fair. (As noted in footnote 3, Geiser and Studley moderated this conclusion somewhat in a later publication.) When we conducted analyses within campuses and cohorts, with each test component considered separately, however, we did not find the same pattern of results. In general, adding parental income and education to the model led to an increase in R^2 of only .004. Although slight changes in the regression coefficients occurred, as one would expect, the coefficients for the SAT I were not generally more affected by the introduction of the socioeconomic status variables than the coefficients for the SAT II. On average, the coefficients of the individual predictors changed by no more than .02. The average coefficients for the SAT I Verbal and SAT II Writing tests decreased trivially, while the average coefficient for HSGPA and for the SAT II third test increased trivially. For the remaining variables, the average coefficients stayed the same to two decimal places.

e. *Whether the SAT I or the SAT II was used in predicting UCGPA, White students’ grades were usually underpredicted by at least .05 (in grade points) when a common regression equation was used for all students, while Hispanic and Asian-American students’ grades were often overpredicted by at least that amount. Both underprediction and overprediction occurred for African Americans.* Incorporating parental income and education into the prediction equation did not substantially alter the pattern of prediction errors. Overprediction of GPAs for African-American and Hispanic students has been common in past research, and has been attributed to a wide variety of factors ranging from incomplete specification of regression models and the unreliability of predictor variables to the particular challenges faced by students of color in the college environment. Overprediction of Asian-Americans’ GPAs is more unusual, and may be related to the language background of Asian-American students in California. Some recent research findings (Zwick & Schlemmer, 2004) suggest that college grades may

tend to be underpredicted for Asian-Americans whose first language is English, while grades for other Asian-American students tend to be overpredicted.

5.1. *Limitations and Future Research Plans*

This study was limited by the nature of the available data. For example, the data set did not include gender and primary language, which may substantially affect the prediction of UCGPA. Also absent from the data set was the identity of the SAT II third test taken by each student. In addition, because demographic information was not available on the 10,528 cases that were excluded from the UCOP data set, it is impossible to determine the effect of their exclusion. Finally, the unavailability of applicant data made it impossible to consider the application of range restriction corrections. These adjustments are sometimes applied in admissions research to adjust for the restriction of range (of test scores and HSGPA, and, as a result, of college grades as well) that occurs because students whose SATs or high school grades are too low to allow admission will not have freshman GPAs. In general, range restriction curtails the size of the observed correlations between predictor variables and college GPA. The apparent association of test scores and HSGPA with college GPA is therefore smaller than it would be if all applicants could be considered (see Gulliksen, 1987, Chapter 13; Howell, 1997, pp. 266-267). Statistical procedures have been developed to estimate the correlations for the full population of applicants. These range restriction corrections are only approximate at best, however, because they rely on unrealistically simple assumptions about the selection process (see Rothstein, 2004, for an interesting consideration of this issue). Nevertheless, the corrections may facilitate comparisons among institutions or student groups that are affected to varying degrees by range restriction (Ramist et al., 1994, p. 5; see also Kobrin, Camara, & Milewski, 2004).¹⁰

A subsequent article will describe additional analyses of the UC data using hierarchical linear modeling. This approach can better reflect the structure of the data, in which students are “nested” within campuses and cohorts. The first level of the model describes the regression of students’ UCGPAs on a set of predictors within the 28 campus-cohort combinations. The second level of the model describes the dependence of the level-1 regression coefficients on predictors that are defined at the campus-cohort level, such as admission rate and average test score.

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¹⁰ Geiser and Studley elected not to use range restriction corrections in their validity analyses (2001, p. 4), which was a reasonable decision in a study that did not focus on comparisons among UC campuses, cohorts, or other student groups.

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TABLES

Table 1A

Number of Students in Each Cohort and Campus

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB	Total
1996	3461	3204	3009	3595	1178	2387	3142	19976
1997	2830	2271	1859	2949	1736	2464	2221	16330
1998	3579	3333	2964	4058	1951	3181	3349	22415
1999	3490	3108	3537	4034	2417	2925	3569	23080
Total	13360	11916	11369	14636	7282	10957	12281	81801

Table 1B

Number of Students Providing Income and Parental Education Information

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB	Total
1996	2950	2881	2769	3204	1152	2131	2803	17890
1997	2472	2057	1714	2609	1688	2202	1953	14695
1998	2765	2806	2491	3304	1852	2565	2695	18478
1999	2815	2597	3065	3356	2339	2445	2930	19547
Total	11002	10341	10039	12473	7031	9343	10381	70610

Table 1C
Admission Rates for Each Cohort and Campus

	Applications	Admissions	Admission Rates
<u>UCB</u>			
1996	6242	2081	0.33
1997	5937	2211	0.37
1998	5987	2108	0.35
1999	6319	2036	0.32
<u>UCD</u>			
1996	4641	3251	0.70
1997	4463	3076	0.69
1998	4241	2895	0.68
1999	4474	2842	0.64
<u>UCI</u>			
1996	4190	2566	0.61
1997	3778	2152	0.57
1998	3752	2028	0.54
1999	4170	2467	0.59
<u>UCLA</u>			
1996	7760	3531	0.46
1997	7052	3049	0.43
1998	7505	2840	0.39
1999	8488	3285	0.39
<u>UCR</u>			
1996	2814	2289	0.81
1997	2407	2148	0.89
1998	2503	2034	0.81
1999	2927	2431	0.83
<u>UCSD</u>			
1996	4050	2337	0.58
1997	3951	2399	0.61
1998	4187	2308	0.55
1999	4680	2569	0.55
<u>UCSB</u>			
1996	4891	3588	0.73
1997	4485	3208	0.72
1998	4751	3281	0.69
1999	5330	3550	0.67

Table 2A

Means and Standard Deviations (parenthesized) for HSGPA

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	4.01 (.42)	3.76 (.37)	3.67 (.37)	3.99 (.38)	3.53 (.44)	3.95 (.32)	3.52 (.39)
1997	4.10 (.37)	3.79 (.38)	3.73 (.35)	4.08 (.33)	3.48 (.43)	3.96 (.31)	3.59 (.39)
1998	4.12 (.38)	3.76 (.36)	3.73 (.32)	4.09 (.35)	3.51 (.39)	3.94 (.32)	3.66 (.37)
1999	4.16 (.39)	3.75 (.37)	3.62 (.43)	3.70 (.27)	3.53 (.41)	4.03 (.28)	3.72 (.38)

Table 2B

Means and Standard Deviations (parenthesized) for SAT I Verbal Score

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	634.3 (89.0)	564.4 (86.6)	528.7 (87.5)	604.3 (80.5)	512.0 (93.2)	593.8 (82.6)	550.1 (80.3)
1997	651.4 (87.1)	569.9 (89.4)	537.4 (85.1)	615.1 (76.0)	511.5 (97.9)	603.9 (77.3)	572.7 (82.4)
1998	651.5 (87.3)	557.2 (91.1)	537.9 (80.4)	622.2 (77.0)	512.9 (93.9)	603.1 (78.3)	570.9 (78.8)
1999	639.6 (94.1)	563.7 (92.8)	557.7 (76.3)	620.7 (80.8)	507.7 (96.0)	608.9 (82.7)	578.9 (81.2)

Table 2C

Means and Standard Deviations (parenthesized) for SAT I Math Score

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	666.6 (91.2)	603.3 (75.8)	593.6 (83.7)	635.1 (84.4)	550.6 (94.8)	634.0 (74.8)	569.9 (79.4)
1997	687.4 (83.6)	614.5 (74.8)	599.8 (79.8)	655.6 (74.9)	561.2 (95.3)	646.5 (73.1)	598.2 (76.5)
1998	685.5 (79.9)	596.2 (80.6)	593.1 (84.0)	654.3 (79.4)	557.8 (91.2)	641.8 (72.7)	594.2 (77.8)
1999	670.8 (89.0)	601.8 (82.6)	603.5 (82.2)	655.5 (85.2)	552.5 (95.0)	648.2 (74.1)	602.5 (79.7)

Table 2D

Means and Standard Deviations (parenthesized) for SAT II Writing Score

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	609.9 (93.1)	537.7 (86.3)	500.0 (81.7)	577.9 (87.6)	483.9 (84.8)	567.3 (84.7)	523.0 (81.9)
1997	632.4 (91.1)	545.7 (86.4)	507.8 (84.2)	598.2 (79.9)	484.1 (89.4)	579.6 (78.9)	542.2 (82.0)
1998	630.0 (92.3)	529.8 (91.4)	507.1 (80.9)	601.1 (86.6)	482.8 (87.0)	574.4 (83.6)	540.2 (82.8)
1999	641.5 (100.6)	557.8 (94.2)	543.4 (82.4)	622.5 (91.0)	500.6 (86.5)	605.4 (88.5)	571.5 (85.8)

Table 2E

Means and Standard Deviations (parenthesized) for SAT II Math Score

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	652.3 (95.5)	588.6 (79.8)	577.1 (84.0)	618.7 (89.5)	532.7 (93.6)	618.3 (77.2)	547.1 (81.9)
1997	670.8 (92.3)	594.9 (79.5)	575.8 (84.3)	634.0 (81.1)	544.2 (94.5)	623.3 (77.2)	571.7 (82.1)
1998	672.3 (88.1)	579.2 (85.9)	573.3 (86.5)	635.5 (87.1)	537.3 (89.3)	624.5 (78.1)	570.7 (82.4)
1999	664.3 (98.0)	588.1 (87.4)	587.9 (88.5)	643.6 (91.8)	538.7 (91.2)	636.9 (79.8)	583.4 (85.0)

Table 2F

Means and Standard Deviations (parenthesized) for SAT II Third Test Score

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	661.7 (97.6)	585.2 (99.4)	572.2 (112.7)	627.1 (94.7)	547.9 (117.9)	605.9 (92.1)	549.7 (98.5)
1997	682.1 (89.3)	598.2 (97.3)	576.1 (108.6)	641.5 (85.5)	553.6 (118.4)	617.7 (86.1)	577.5 (93.9)
1998	677.8 (90.9)	584.9 (106.4)	577.9 (109.7)	646.6 (88.4)	561.2 (117.0)	616.5 (91.3)	581.5 (97.4)
1999	671.5 (98.2)	588.8 (106.8)	585.5 (109.4)	644.7 (96.0)	557.9 (123.3)	643.1 (93.8)	586.9 (98.2)

Table 2G

Means and Standard Deviations (parenthesized) for UCGPA

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	3.06 (.62)	2.78 (.64)	2.75 (.62)	3.00 (.59)	2.51 (.78)	2.93 (.58)	2.78 (.58)
1997	3.16 (.58)	2.84 (.62)	2.87 (.57)	3.08 (.53)	2.51 (.75)	2.97 (.53)	2.88 (.57)
1998	3.14 (.58)	2.79 (.64)	2.81 (.59)	3.10 (.55)	2.48 (.73)	2.96 (.56)	2.92 (.56)
1999	3.10 (.61)	2.73 (.68)	2.74 (.63)	3.09 (.58)	2.52 (.81)	3.00 (.55)	2.92 (.59)

Table 2H

Means and Standard Deviations (parenthesized) for Income (in dollars)

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	82,360 (81,736)	74,908 (67,125)	61,443 (58,025)	74,995 (72,788)	56,687 (71,873)	79,903 (66,431)	81,850 (71,220)
1997	89,518 (94,649)	78,419 (69,501)	62,952 (61,525)	81,682 (76,267)	54,218 (64,054)	89,766 (86,282)	90,378 (75,564)
1998	86,120 (81,746)	72,396 (64,608)	65,975 (63,559)	78,848 (79,860)	48,681 (52,464)	82,299 (76,495)	87,901 (71,518)
1999	82,100 (79,311)	77,232 (69,975)	70,355 (68,879)	80,436 (82,792)	53,119 (59,135)	81,422 (74,706)	86,068 (74,431)

Table 2I

Means and Standard Deviations (parenthesized) for Parent Education

Year	UCB	UCD	UCI	UCLA	UCR	UCSD	UCSB
1996	16.3 (3.1)	15.7 (3.4)	15.2 (3.2)	15.7 (3.4)	14.7 (3.5)	16.3 (3.0)	16.2 (3.0)
1997	16.6 (3.1)	16.0 (3.3)	15.3 (3.2)	16.3 (3.2)	14.6 (3.5)	16.5 (2.9)	16.5 (2.9)
1998	16.6 (3.0)	15.4 (3.4)	15.2 (3.2)	16.0 (3.2)	14.6 (3.5)	16.3 (2.9)	16.3 (3.0)
1999	16.1 (3.4)	15.5 (3.5)	15.5 (3.1)	15.9 (3.3)	14.6 (3.4)	16.1 (3.1)	16.2 (3.1)

Table 3
Predictors Used in the Initial Set of Regression Models

Model	HS GPA	SAT I: Verbal	SAT I: Math	SAT II: Writing	SAT II: Math	SAT II: Third	Parent income	Parent education
1	X							
2		X	X					
3				X	X			
4				X	X	X		
5		X	X	X	X	X		
6	X	X	X					
7	X			X	X			
8	X			X	X	X		
9	X	X	X	X	X	X		
10	X	X	X	X	X	X	X	X

Table 4
 R^2 Values for Each Campus and Cohort - Models 1-8

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
UCB								
1996	0.122	0.090	0.118	0.132	0.132	0.149	0.166	0.174
1997	0.135	0.088	0.117	0.127	0.129	0.153	0.173	0.178
1998	0.085	0.071	0.098	0.111	0.112	0.112	0.129	0.138
1999	0.097	0.112	0.137	0.147	0.147	0.146	0.163	0.171
UCD								
1996	0.129	0.092	0.121	0.139	0.139	0.191	0.209	0.224
1997	0.162	0.067	0.095	0.127	0.127	0.197	0.209	0.237
1998	0.145	0.139	0.167	0.200	0.201	0.228	0.244	0.269
1999	0.136	0.083	0.112	0.130	0.130	0.190	0.202	0.218
UCI								
1996	0.114	0.076	0.110	0.117	0.120	0.180	0.199	0.205
1997	0.148	0.132	0.141	0.163	0.170	0.225	0.225	0.243
1998	0.073	0.092	0.119	0.128	0.129	0.139	0.158	0.166
1999	0.049	0.080	0.096	0.103	0.106	0.117	0.130	0.137
UCLA								
1996	0.167	0.138	0.152	0.163	0.168	0.215	0.224	0.231
1997	0.113	0.085	0.110	0.122	0.125	0.159	0.179	0.187
1998	0.124	0.092	0.112	0.128	0.129	0.167	0.179	0.191
1999	0.096	0.100	0.123	0.132	0.134	0.159	0.175	0.181
UCR								
1996	0.197	0.134	0.142	0.153	0.159	0.244	0.241	0.247
1997	0.127	0.103	0.108	0.111	0.119	0.187	0.183	0.185
1998	0.133	0.053	0.072	0.077	0.080	0.169	0.173	0.176
1999	0.113	0.064	0.076	0.079	0.081	0.157	0.155	0.158
UCSD								
1996	0.078	0.065	0.084	0.094	0.094	0.131	0.146	0.155
1997	0.119	0.043	0.065	0.082	0.084	0.152	0.168	0.182
1998	0.096	0.051	0.070	0.088	0.089	0.145	0.159	0.174
1999	0.068	0.074	0.097	0.105	0.105	0.140	0.153	0.163
UCSB								
1996	0.168	0.118	0.132	0.139	0.143	0.242	0.244	0.249
1997	0.165	0.068	0.096	0.103	0.104	0.217	0.229	0.233
1998	0.153	0.073	0.093	0.099	0.102	0.196	0.207	0.213
1999	0.166	0.083	0.101	0.102	0.107	0.219	0.223	0.225
Median	0.126	0.084	0.110	0.125	0.126	0.168	0.179	0.186

Table 5

Standardized Regression Coefficients from Geiser and Studley for Prediction Models With and Without Parental Income and Education (for all UC Campuses, 1996-1999)

Regression Model:	HS GPA	SAT I	SAT II	Parent Income	Parent Education
Without Income and Education	.27	.07	.23	X	X
With Income and Education	.28	.02	.24	.03	.06

Note: This table contains the same information as Table 6 of Geiser & Studley (2001, October, p. 8).

Table 6
Regression Results for Each Campus and Cohort - Model 9

	HS GPA	SAT I Verbal	SAT I Math	SAT II Writing	SAT II Math	SAT II Third	R ²
UCB							
1996	.25*	-.01	-.04	.21*	-.01	.12*	.176
1997	.27*	-.05	.01	.21*	-.03	.09*	.174
1998	.20*	-.01	-.10*	.18*	.08	.13*	.145
1999	.19*	.02	-.03	.20*	.05	.11*	.174
UCD							
1996	.31*	.00	.05	.20*	.02	.14*	.229
1997	.34*	.01	.01	.13*	.02	.18*	.229
1998	.28*	.03	-.01	.20*	.06	.18*	.270
1999	.30*	.05	.04	.15*	.00	.13*	.215
UCI							
1996	.30*	.08*	-.05	.19*	.12*	.07*	.203
1997	.30*	.13*	.02	.11*	.04	.14*	.254
1998	.20*	.05	-.01	.18*	.09*	.10*	.167
1999	.19*	.06	-.02	.15*	.11*	.09*	.137
UCLA							
1996	.29*	.05	.06	.15*	.03	.08*	.235
1997	.27*	.03	.02	.21*	-.02	.10*	.188
1998	.27*	.04	.04	.16*	-.02	.11*	.186
1999	.22*	.09*	-.01	.18*	.01	.07*	.174
UCR							
1996	.34*	.04	.14*	.15*	-.06	.06	.263
1997	.29*	.13*	.08	.10*	-.03	.04	.192
1998	.34*	.10*	-.02	.14*	-.02	.04	.188
1999	.30*	.07	.10*	.11*	-.04	.05	.166
UCSD							
1996	.25*	.04	-.04	.12*	.15*	.10*	.157
1997	.32*	.01	-.05	.15*	.09*	.13*	.183
1998	.29*	.01	-.03	.18*	.07	.14*	.176
1999	.25*	.01	.09*	.18*	.03	.11*	.160
UCSB							
1996	.35*	.11*	.05	.14*	.03	.07*	.265
1997	.36*	.06	.04	.17*	.03	.07*	.240
1998	.34*	.07*	.01	.17*	.01	.06*	.217
1999	.36*	.13*	-.03	.13*	.05	.02	.234
<u>Median</u>	.29	.05	.01	.17	.03	.10	.188

* Regression coefficient is statistically significant at $\alpha=.01$.

Table 7
Regression Results for Each Campus and Cohort - Model 10

	HS GPA	SAT I Verbal	SAT I Math	SAT II Writing	SAT II Math	SAT II Third	Parent income	Parent Education	R ²
UCB									
1996	.25*	-.02	-.05	.20*	-.01	.13*	.02	.03	.178
1997	.27*	-.06	-.00	.19*	-.03	.11*	.02	.06	.178
1998	.21*	-.03	.11*	.16*	.07	.14*	.06*	.06	.153
1999	.20*	-.02	.05	.17*	.05	.13*	.06*	.07*	.183
UCD									
1996	.31*	-.02	.04	.19*	.02	.15*	.00	.06*	.232
1997	.35*	-.00	.01	.12*	.02	.19*	.01	.05	.232
1998	.29*	.01	-.02	.19*	.06	.19*	.06*	.02	.274
1999	.30*	.04	.03	.14*	.00	.14*	.01	.04	.217
UCI									
1996	.30*	.07*	-.06	.18*	.12*	.08*	-.01	.04	.204
1997	.30*	.12*	.02	.10*	.04	.15*	-.01	.04	.255
1998	.21*	.05	-.02	.18*	.09*	.10*	-.01	.04	.168
1999	.19*	.05	-.03	.14*	.11*	.09*	.01	.06*	.140
UCLA									
1996	.29*	.03	.03	.13*	.03	.10*	.01	.09*	.241
1997	.28*	.01	.01	.19*	-.02	.11*	.06*	.05	.195
1998	.28*	.01	.03	.14*	-.02	.13*	.06*	.04	.192
1999	.23*	.07*	-.02	.16*	.01	.09*	.03	.08*	.181
UCR									
1996	.35*	.03	.14*	.14*	-.06	.06	.01	.01	.263
1997	.29*	.11*	.07	.09	-.03	.05	.04	.03	.195
1998	.34*	.09	-.03	.13*	-.02	.05	.06	.01	.192
1999	.30*	.07	.11*	.12*	-.04	.04	.01	-.03	.167
UCSD									
1996	.26*	.02	-.05	.10*	.14*	.11*	.02	.10*	.166
1997	.32*	-.01	-.06	.14*	.08*	.13*	.03	.06	.188
1998	.30*	-.01	-.04	.16*	.06	.15*	.04	.05	.180
1999	.24*	-.02	.07	.15*	.03	.12*	.07*	.07*	.171
UCSB									
1996	.35*	.09*	.03	.13*	.04	.08*	.03	.05	.269
1997	.36*	.04	.02	.15*	.03	.08*	.02	.06	.244
1998	.34*	.05	-.02	.15*	.01	.08*	.04	.09*	.227
1999	.36*	.12*	-.05	.11*	.05	.04	.02	.06*	.238
<u>Median</u>	.30	.03	.01	.15	.03	.11	.02	.05	.194

* Regression coefficient is statistically significant at $\alpha=.01$.

Table 8A

Prediction Accuracy Results for UC Berkeley: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	321	-0.0253	African American	206	0.0165
Asian American	2779	-0.0459	Asian American	3207	-0.0415
Hispanic	810	-0.0459	Hispanic	570	-0.1054
White	1878	0.0857	White	2124	0.0727

Table 8B

Prediction Accuracy Results for UC Berkeley: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	321	-0.0223	African American	206	0.0240
Asian American	2779	-0.0391	Asian American	3207	-0.0436
Hispanic	810	-0.0344	Hispanic	570	-0.0941
White	1878	0.0722	White	2124	0.0710

Table 9A

Prediction Accuracy Results for UC Davis: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	109	0.0008	African American	160	0.0811
Asian American	2196	-0.0757	Asian American	2532	-0.0663
Hispanic	443	0.0390	Hispanic	608	0.0023
White	2358	0.0616	White	2440	0.0558

Table 9B

Prediction Accuracy Results for UC Davis: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	109	-0.0069	African American	160	0.0846
Asian American	2196	-0.0648	Asian American	2532	-0.0682
Hispanic	443	0.0343	Hispanic	608	-0.0014
White	2358	0.0545	White	2440	0.0569

Table 10A

Prediction Accuracy Results for UC Irvine: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	72	-0.0175	African American	133	-0.0232
Asian American	3219	-0.0429	Asian American	3662	-0.0452
Hispanic	428	-0.0103	Hispanic	717	-0.0367
White	893	0.1466	White	1318	0.1200

Table 10B

Prediction Accuracy Results for UC Irvine: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	72	-0.0317	African American	133	-0.0115
Asian American	3219	-0.0392	Asian American	3662	-0.0435
Hispanic	428	-0.0122	Hispanic	717	-0.0350
White	893	0.1366	White	1318	0.1127

Table 11A
Prediction Accuracy Results for UCLA: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	319	-0.0338	African American	279	-0.0919
Asian American	2622	-0.0805	Asian American	3293	-0.0602
Hispanic	1004	-0.0496	Hispanic	898	-0.0935
White	2129	0.1120	White	2582	0.1073

Table 11B
Prediction Accuracy Results for UCLA: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	319	-0.0409	African American	279	-0.0772
Asian American	2622	-0.0680	Asian American	3293	-0.0545
Hispanic	1004	-0.0509	Hispanic	898	-0.0899
White	2129	0.0994	White	2582	0.0970

Table 12A

Prediction Accuracy Results for UC Riverside: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	110	0.0583	African American	219	-0.0003
Asian American	1506	-0.0346	Asian American	2061	-0.0266
Hispanic	486	-0.0146	Hispanic	856	0.0022
White	660	0.0796	White	844	0.0609

Table 12B

Prediction Accuracy Results for UC Riverside: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	110	0.0471	African American	219	-0.0091
Asian American	1506	-0.0257	Asian American	2061	-0.0216
Hispanic	486	-0.0353	Hispanic	856	-0.0069
White	660	0.0751	White	844	0.0561

Table 13A

Prediction Accuracy Results for UC San Diego: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	83	-0.1021	African American	72	0.0432
Asian American	1953	-0.0321	Asian American	2433	-0.0460
Hispanic	416	-0.0713	Hispanic	503	-0.0697
White	2022	0.0409	White	2309	0.0585

Table 13B

Prediction Accuracy Results for UC San Diego: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	83	-0.0782	African American	72	0.0530
Asian American	1953	-0.0305	Asian American	2433	-0.0463
Hispanic	416	-0.0555	Hispanic	503	-0.0651
White	2022	0.0349	White	2309	0.0566

Table 14A

Prediction Accuracy Results for UC Santa Barbara: Model 6

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	135	-0.0042	African American	173	-0.0065
Asian American	948	-0.0965	Asian American	1048	-0.0920
Hispanic	663	-0.0432	Hispanic	950	-0.0828
White	3349	0.0353	White	3811	0.0366

Table 14B

Prediction Accuracy Results for UC Santa Barbara: Model 7

1996-1997			1998-1999		
Ethnicity	<i>n</i>	Observed minus predicted UCGPA	Ethnicity	<i>n</i>	Observed minus predicted UCGPA
African American	135	-0.0233	African American	173	-0.0138
Asian American	948	-0.0904	Asian American	1048	-0.0942
Hispanic	663	-0.0558	Hispanic	950	-0.0819
White	3349	0.0362	White	3811	0.0348

Figure 1 (Model 6)

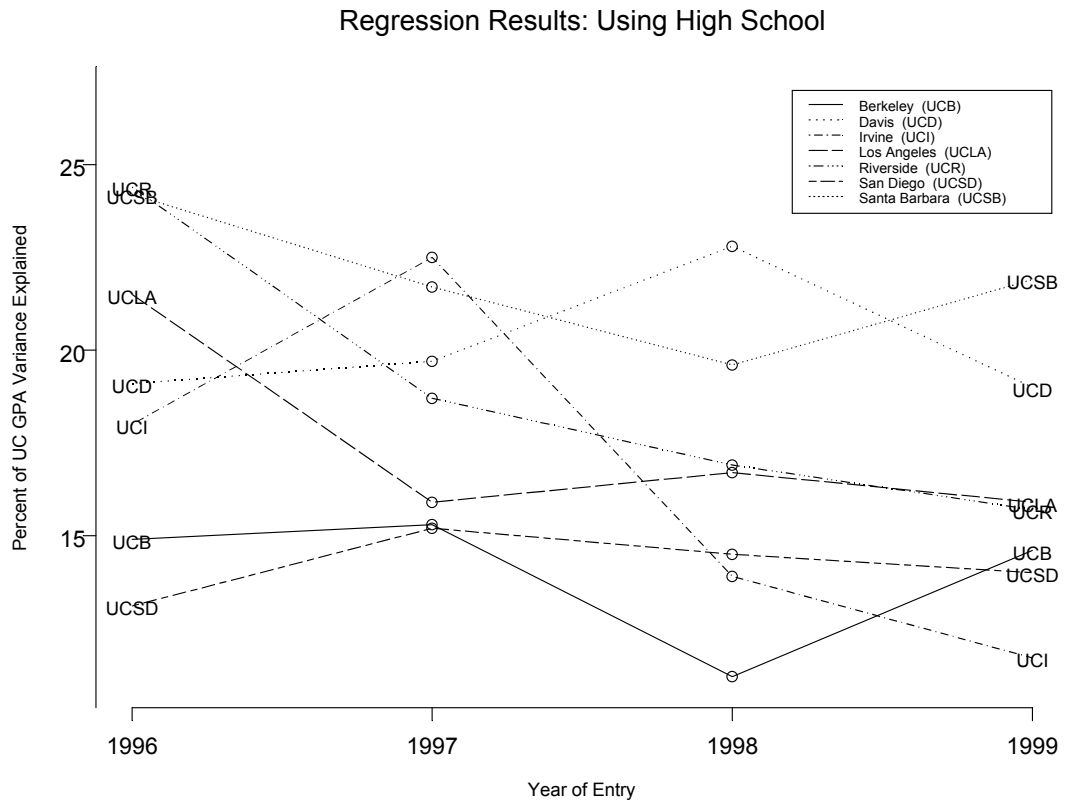


Figure 2 (Model 7)

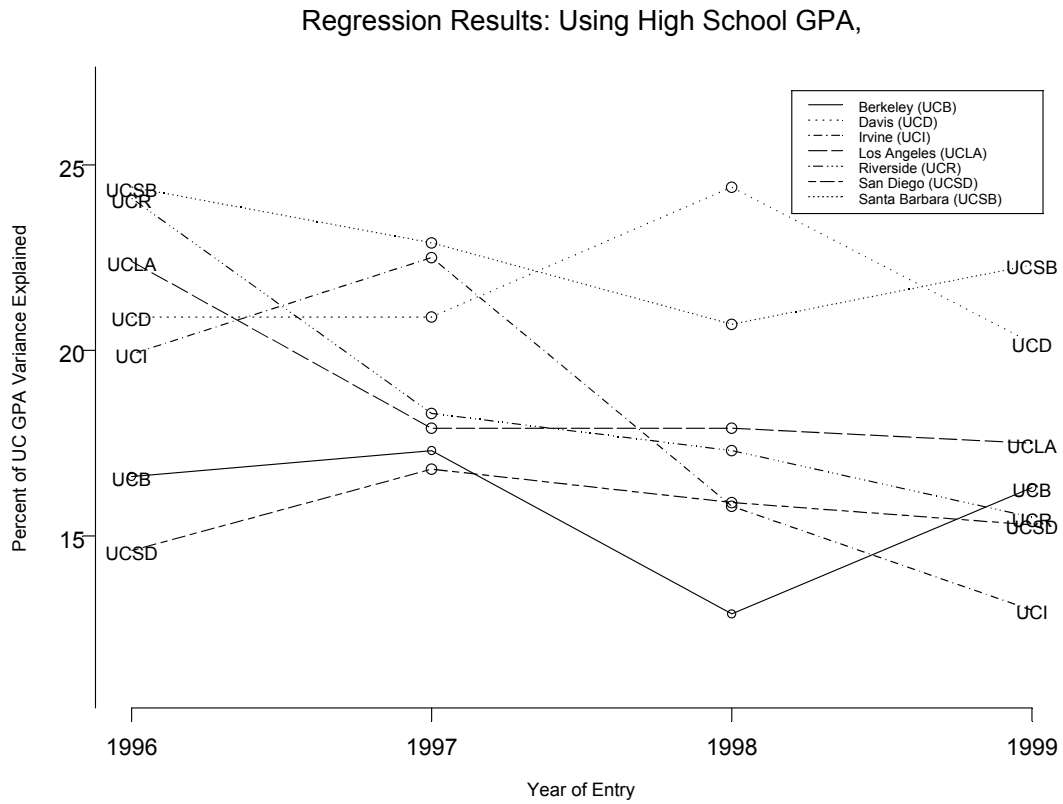


Figure 3 (Model 8)

