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## ABSTRACT

Emphasizing graduation rate, W. Bowen and D. Bok (1998) argue that "race-sensitive" admission at selective colleges enhances the educational attainment of underrepresented minority students, and that the effect increases with college selectivity. Focusing on graduation in science, however, R. Elliott and colleagues (1995) conclude that: (1) preferential admission explains lower rates for underrepresented minority groups; and (2) students of given interest and preparation will fare better at less selective colleges. These hypotheses were examined using Bowen and Bok's "College & Beyond" data from 24 institutions. Among students initially intending science, blacks were less likely than whites to graduate in science (40% versus 56%), and women less likely than men (47% versus 61%). Consistent with the first conclusion of Elliot et al., differences in Scholastic Assessment Test mathematics scores fully accounted for the ethnic disparity and reduced the gender disparity. Support was not found for a positive effect of college selectivity. The estimated effect was negative, though this is qualified by the study's restricted selectivity range and correlational design. A prospective science student is advised to choose the college where students with academic qualifications and interests similar to his or her own fare best in science. Four appendixes contain technical notes; a discussion of science, mathematics, and engineering definitions; and tables of study data. (Contains 4 tables, 9 figures, and 52 references.) (SLD)

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Ethnic and Gender Differences in Science Graduation at Selective Colleges  
with Implications for Admission Policy and College Choice

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## Abstract

Emphasizing graduation rate, Bowen and Bok (1998) argue that “race-sensitive” admission at selective colleges enhances the educational attainment of underrepresented minority students, and that the effect increases with college selectivity. Focusing on graduation in science, however, Elliott and colleagues (1995) conclude that (1) preferential admission explains lower rates for underrepresented minority groups, and (2) students of given interest and preparation will fare better at *less* selective colleges. We examined these hypotheses using Bowen and Bok’s “College & Beyond” data from 24 institutions. Among students initially intending science, Blacks were less likely than Whites to graduate in science (40% vs. 56%), and women less likely than men (47% vs. 61%). Consistent with Elliott et al.’s first conclusion, differences in SAT mathematics scores fully accounted for the ethnic disparity and reduced the gender disparity. Support was not found for a positive effect of college selectivity. The estimated effect was negative, though this is qualified by the study’s restricted selectivity range and correlational design. A prospective science student is advised to choose the college where students with academic qualifications and interests similar to his or her own fare best in science.

Ethnic and Gender Differences in Science Graduation at Selective Colleges  
with Implications for Admission Policy and College Choice

Demand is high for citizens with college-level training in science and mathematics. Their skills are seen as vital to American health, economic and security interests, and careers requiring these skills are disproportionately judged among the most prestigious (Nakao & Treas, 1990; National Science Board-NSB, 2002). Yet despite decades of effort at institutional, state and national levels, women, Blacks, Hispanics and American Indians remain substantially underrepresented among college graduates with science, math or engineering (SME) degrees (National Science Foundation-NSF, 1992; NSB, 2002). This concerns many in the diverse communities of behavioral science, business, civil rights, education and science, suggesting lost personal and group opportunity, inhibition of national productivity and of the advancement of science, generally (Chipman & Thomas, 1987). And as traditionally underrepresented racial and ethnic minority students make up a steadily increasing proportion of the United States' college-age population, the challenges presented by these trends become still more significant (NSB, 2002). In terms simply of numbers, college-level attrition from science is but the tip of an iceberg—far greater losses from the potential pool of scientifically talented and interested people occur in the years *prior* to the traditional age of college entry (Chipman & Thomas, 1987; Meece, Parsons, Kaczala, Goff, & Futterman, 1982; Oakes, 1990). Yet reducing the loss during college has figured prominently in policy objectives, since students who enter college with science aspirations tend to be highly able (Astin & Astin, 1993; Green, 1989) and have interest that has weathered the many pre-college pressures to pursue a less demanding course. More than half will not persist in SME, with greater losses among Blacks and Hispanics (Astin & Astin, 1993; Green, 1989; National Academy of Sciences, 1987).

### Underrepresented Minorities and College Science

The National Science Foundation (1992) reports that among 1980 high school graduates who planned a SME major and immediately began higher education, 35% of Whites, but just 16% of Blacks earned a bachelor's degree (in any field) 4<sup>1</sup>/<sub>2</sub> years later. The same report notes that Blacks' July 1983 representation in the population of all 18 and 19 year-olds (14.4%) is substantially greater than their representation among those intending a SME major and entering four-year colleges that autumn (9.4%). Six years later, Blacks' share of BAs awarded in SME was still less representative (5.2%). Among a sample of  $N > 26,000$  students entering 4-year colleges in 1985, Astin and Astin (1993) also found disproportionate losses from SME majors for minority students and women. The ratio of within-ethnicity SME graduation percentage to within-ethnicity percentage initially planning a SME major<sup>1</sup> was .37 for Chicanos, .47 for African Americans, .51 for American Indians, .61 for Whites and .68 for Asians. Within-gender ratios were .63 for men, .48 for women. Longitudinal data from a more recent NSF report (1999) are shown in Table 1. Among 22-24 year-olds between 1990 and 1994, increases in the within-ethnicity proportions of Blacks and Hispanics completing engineering and natural sciences degrees, regardless of gender, were less than those among Asians and Whites. And within all ethnic groups except Blacks, males had greater increases than females. Thus, despite concerted programmatic efforts and billions of dollars spent to ameliorate the disproportionate shortage of women and traditionally underrepresented minority students in the sciences (Culotta & Gibbons, 1992; Seymour & Hewitt, 1997), their relative representation with respect to SME bachelor's degree attainment may not be improving.

### Intention to Major in Science

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<sup>1</sup> We recognize that this ratio is different from "SME persistence" as usually defined, which is the proportion of initial SME-intenders who graduate in SME. The ratio reported here includes all SME graduates in the numerator, regardless of initial intent.

Intention and level of commitment to goals figures prominently in Tinto's (1993) model of overall college persistence. Elliott, Strenta, Adair, Matier and Scott (1995) found that "...intention to concentrate in science is by far the strongest predictor of actually doing so..." (p. 10). Blacks' rate of initial intent to major in SME is consistently found to be similar to or higher than that of Whites (Astin & Astin, 1993; Dunteman et al., 1979; Elliott et al., 1995; Ethington, 1988; NSB, 2002; Oakes, 1990; Ware & Lee, 1988). In their study of 4-year college students matriculating in 1985, Astin and Astin (1993) found roughly equal rates of SME intent, at about 35%, for Black, Hispanic and American Indian freshmen, compared with 27% for Whites and 53% for Asians. Women, however, are consistently found less likely than men to intend a SME major, though gender differences vary substantially within SME sub-disciplines (Astin & Astin, 1993; DeBoer, 1986; Eccles & Hoffman 1984; NSB, 2002; Turner & Bowen, 1999; Ware & Lee, 1988). Astin and Astin found that 40% of men planned a SME major, compared with 21% of women. More recent and nationally representative data from the National Science Board (2002) suggest that the gender effect is greater for Whites (30.3% of males intended SME, 12.9% of females) than for Blacks (31.8% of males, 18.9% of females).

#### Pre-college Mathematics Preparation

Despite the consistent evidence of large ethnic differences in SME persistence, ethnicity, *per se*, is *not* significantly associated with persistence when academic preparation is taken into account (Adair, 1991; Astin & Astin, 1993; Dunteman, Wisenbaker, & Taylor, 1979; Elliot et al., 1995; Hilton, Hsia, Solorzano, & Benton, 1989; Ware & Lee, 1988). These quantitative studies of undergraduate SME persistence vary in terms of samples and methods, but measures of pre-college academic preparation, especially in math and science (e.g., standardized test scores, number of relevant courses, and grades), figure prominently in all of the predictive equations while ethnicity

drops out. Astin and Astin (1993) assert, “The strongest and most consistent predictor of changes in students’ interest in science majors or careers is the students’ entering level of mathematical and academic competency...” (p. 2). Higher levels, they report, are strongly associated with SME persistence, as well as with movement into SME from undecided or non-science majors.

Underrepresented minority students are consistently found to have significantly lower means on such pre-college academic measures (Bowen & Bok, 1998; Dunteman et al., 1979; Elliott et al., 1995; Ramist, Lewis, & McCamley-Jenkins, 1994). Most studies find that gender differences favoring males in SME persistence, like those favoring Whites and Asians, are largely accounted for by differences in pre-college and college academic measures (e.g., Adair, 1991; Astin & Astin, 1993; Strenta, Elliott, Adair, Matier & Scott, 1994; Turner and Bowen, 1999). But several identify a remaining direct effect of gender, usually when predicting persistence in certain sub-categories of SME (Dunteman et al., 1979; Levin & Wyckoff, 1995; Strenta et al., 1994).

#### Institutional Selectivity, Affirmative Action, and the “Frog Pond” Hypothesis

Among students intending a SME major at the four elite institutions studied by Elliott et al. (1995), differences on measures of math preparation between Black and White students were greater than those found in a sample more representative of all college-going students studied by Dunteman et al. (1979). Using the *SD* for all SME-intending students in their sample, Elliott et al. found that Blacks and Hispanics averaged, respectively, 1.7 and 1 *SDs* lower than Whites and Asians (together) on an “academic index” comprised of SATM, SATV, three College Board Achievement Tests, and high school GPA. They note that these gaps would increase by 15% to 20% if the White-Asian *SD* is used. When these measures were held constant, ethnic classification failed to account for significant variation in SME persistence. That is, differences in standard measures of pre-college math, science and general academic achievement were sufficient to account for the large

ethnic group differences in persistence among SME-intenders (e.g., SME graduation rates of 34% among Blacks, 61% among Whites) and also among those *not* initially intent on SME; 3% of Blacks but 9% of Whites shifted into a SME field by the senior year.

Elliott and his colleagues (1995) conclude that affirmative action admission policies for underrepresented minority students are responsible for the large ethnic differences in measures of pre-college achievement at these highly selective institutions. They argue that the resulting mismatches between institutional competitiveness and individual preparation are derailing very able minority students from the science track. Having demonstrated both strong science interest and ability (relative, say, to a nationally representative sample of college-bound students), Elliott et al. suggest that relatively less-well-prepared students at these institutions—regardless of ethnicity—would have had a better chance of completing SME majors at less competitive colleges. Figure 1 is a plot of data from 11 other private colleges that Elliott et al. cite as support for this inference. The mean of each third of an institution's SATM distribution is plotted with the associated percentage of the institution's natural science degrees earned by students with scores in that third of the distribution. Elliott et al. note that though SATM score distributions vary considerably across the 11 colleges, the proportions of science degrees awarded by thirds of the SATM distribution are similar, "about 54%, 31%, and 15%" (p. 35)," respectively, to students in the top, middle and bottom thirds of each institution's SATM distribution. Thus, they argue that "...a student with an SATM score of 580 who wants to be in science will be three or four times more likely to persist at institutions J and K, where he or she is competitive, than at institutions A and B, where he or she is not." This relationship holds, they contend, despite the higher overall proportion of students earning science degrees at the more selective institutions (i.e., as noted in Figure 1, of *all* degrees awarded at the five most selective institutions, about 28% were in SME, compared with about 15% at the other



six). For the student with a 580 math SAT score, Elliott et al. remark that "...a 54% chance of getting one of the 15% of the degrees that are in science [at the less selective schools] is nearly twice as good as a 15% chance of getting one of the 28% [at the more selective ones]..." The Elliott et al. inference parallels the "frog pond" social comparison hypothesis that an individual's relative standing in a group with respect to some attribute exerts greater influence on self-assessments concerning the attribute than does an absolute measure of the attribute (e.g., Buunk & Ybema, 1997; Davis, 1966; Kelley, 1952; Marsh, Kong, & Hau, 2000). This theory was invoked by Davis (1966) with respect to within-college effects on the career choices of a national probability sample of male college graduates: "Counselors and parents might well consider the drawbacks as well as the advantages of sending a boy to a 'fine' college, if, when doing so, it is fairly certain he will end up in the bottom ranks of his graduating class" (p. 31).

Bowen and Bok (1998) contend that concern about academic mismatches resulting from affirmative admission policy is unfounded. They emphasize a finding of higher overall graduation rates (without respect to major) for minority students at more selective colleges. This was one of their two major findings about relations between institutional selectivity and academic outcomes for students at 28 moderately to extremely selective institutions. The other finding was a strong negative association of selectivity with a student's percentile rank in class. These relations held for both Blacks and Whites, and within different levels of individual SAT scores. That is, for example, among relatively low scoring students in their sample (<1000 combined V+M SAT), regardless of ethnicity, those who enrolled in colleges with a high mean SAT were more likely to graduate than those in schools with a low mean SAT. Conversely, with eight other variables, including academic and demographic indicators, held constant in a multiple regression model, attendance at the most selective colleges in their sample was associated with a loss of nearly 15 percentage points in

college class rank. Making an argument similar to the one made by Elliott et al. (1995) with respect to SME, Bowen and Bok (1998) offer a contextual rationale to explain the negative relationship between institutional selectivity and percentile academic rank, and its implications for Black students: “The grades earned by Black students at the C&B schools often reflect their struggles to succeed academically in highly competitive academic settings” (p. 72). The mean collegiate class ranks for Blacks and Whites in their study were 23<sup>rd</sup> and 53<sup>rd</sup> percentile, respectively. Bowen and Bok write, “A student with a given SAT score, high school grades, and so on, who attends one of the most selective schools, should be expected to have a lower rank in class than a student with the same credentials who attends a school that enrolled a smaller number of top-rated students. This is precisely the pattern we found” (p. 73). Bowen and Bok express concern about this wider ethnic gap in class rank at more selective schools, and discuss in detail their finding that the Black-White difference in rank is even greater than what would be predicted given Blacks’ lower average standing on relevant pre-college variables. They do not suggest, however, that possible specific *costs* of such lower relative achievement should prompt reformulation of admission policies. Rather, their conclusion about the results of race-sensitive admission turns on the positive association of institutional selectivity with graduation rates:

The fact that graduation rates increase as the selectivity of the college rises and that students of the same academic ability graduate at higher rates when they attend more selective institutions shows that carefully chosen minority students have not suffered from attending colleges heavily populated by White and Asian American classmates with higher standardized test scores. Quite the contrary—they have fared best in such settings (Bowen & Bok, 1998, p. 88).

With respect to distributions of final academic majors, Bowen and Bok (1998) report a finding seemingly quite different from that of Elliott et al. (1995): “Blacks and Whites were equally likely to have majored in philosophy, economics, the natural sciences, and engineering” (p. 71). The basis of this result, however, differs from Elliott et al. in that initial intended major

was not considered, and the within-ethnicity distribution of majors was calculated only among graduates. Furthermore, in contrast to their analyses of overall graduation and rank in class, Bowen and Bok do not report on the distributions of majors as a function of institutional selectivity.

### Description of This Study

In this study we use the data studied by Bowen and Bok (1998) to test in a broader sample of selective colleges two hypotheses suggested by the work of Elliott et al. (1995) and others: (1) differences in pre-college academic preparation and interest will account for ethnic and gender differences in SME graduation rates, and (2) college selectivity, with student characteristics held constant, will be negatively associated with SME graduation. Figure 2 is a path diagram of our hypothesized model, including indications of the expected direction (+ or -) of effects. The direct paths to SME graduation from ethnicity (Black or White) and gender are labeled with zeros, since it is hypothesized that these effects will not be significant once differences in SME preparation and interest are considered. Reflecting findings of both Elliott et al. (1995) and Bowen and Bok (1998), as well as of other college effects researchers, both supportive influences in the college environment and competitive—negative—ones are expected to influence SME graduation and to be positively associated with institutional selectivity (Drew & Astin, 1972; Ethington & Smart, 1986; Pascarella, Smart, Ethington, & Nettles, 1987). Our aim is to assess the net effect of selectivity.

Our methodological goal is to improve on the extant SME-persistence literature by using multilevel or hierarchical linear models to better account for the non-random distribution of students across colleges (e.g., Bock, 1989; Burstein, 1980; Ethington, 1997, Kreft & de Leeuw, 1998; Raudenbush & Bryk, 1986; Snijders & Bosker, 1999). All of the multi-college SME

studies we found in a search of the psychological and educational literature (Astin & Astin, 1993; Dunteman et al., 1979; Elliott et al., 1995; Hilton et al., 1989; Strenta et al., 1994; Ware & Lee, 1988) employed a unilevel approach. That is, even when college-level variables were obtained—e.g., college selectivity—they were treated as if they were characteristics of students, i.e., by assigning each student from a given college that college's value on the variable. Ethington (1997) notes that such disaggregation of “higher order variables to the individual level violates the assumption of independence of observations that is a basic assumption for the classical OLS approach...and results in misestimated standard errors” (p. 167).

## Method

### Participants

The participants in this study are Black and White students who matriculated as college freshmen in 1989 at 24 colleges in the “College and Beyond” (C&B) database assembled by The Andrew W. Mellon Foundation (AMF). For more detailed information on the C&B database, see Bowen and Bok's (1998) Appendix A. These 24 colleges were selected from the total of 34 C&B colleges because in 1989 they also participated in the annual Cooperative Institutional Research Program (CIRP) administered by the Higher Education Research Institute at UCLA. The four-page CIRP questionnaire was administered during freshmen orientation and contained an item central to our investigation: intended academic major. A total of  $N = 28,707$  students enrolled at the 24 C&B/CIRP colleges (unless otherwise noted, all reported  $N$  and analyses are weighted according to AMF instructions to account for sampling design at two of the institutions (see Bowen and Bok, 1998, Appendices A and B). About 53% of these students are women, and the ethnic group percentages are as follows: Asian 8.9, Black 6.4, Hispanic 3.2, Native American 0.3, White 79.3, foreign 0.9, “other” 0.2, and “unknown” 0.9. To focus in a way comparable to

most other studies of SME persistence, analyses here will be limited to non-Hispanic Whites and Blacks,  $n = 24,592$ . Henceforth this group of identified Blacks and Whites at the CIRP schools will be referred to as the *Total* cohort.

### Incomplete Data

We analyzed a subset of the *Total* cohort, comprised only of those participants with valid observations on all variables ( $n = 16,616$  or 68% of the *Total*). To aid in assessing the impact of this loss of data, as well as to position this “*Complete*” cohort against national norms, values of key variables are presented in Table 2 alongside those of the *Total* cohort and of some more nationally representative college-bound cohorts. The 24 CIRP colleges are quite selective by national standards, more than half rated among the “most” selective in the country by the editors of Barron’s Educational Guides (2001). Students in both the *Total* and *Complete* cohorts of this study are substantially more likely than students from more nationally representative samples to initially intend and to complete a SME major, and their SAT math scores are well over a *SD* higher.

By far the greatest source of data shortfall between the *Total* and *Complete* cohorts, and of the different rates of *Complete* cohort representation between Blacks and Whites, was failure to complete a CIRP survey (26% overall, 32% of Blacks, 25% of Whites). After this, losses because of missing values for key variables are modest (89% of those who returned a CIRP survey had complete data on all variables used in this study) and participation of Blacks and Whites is similar. Equal percentages (92%) of Blacks and Whites who completed a CIRP survey had a valid “intended major”; 96% of each group had a valid SAT math score; and 97% and 98%, respectively, of Blacks and Whites had a non-missing value for graduation status. Rates of intention to major in science were the same in the *Total* and *Complete* cohorts (35% of Blacks,

27% of Whites), SAT math means and *SDs* are essentially the same, and SME graduation rate was just one percentage point higher for Blacks in the *Complete* cohort than in the *Total*. Based on more formal analyses of the relation between incomplete data and the variables of interest in this study (see Appendix A), we will assume that these data are “missing-completely-at-random” (Little & Rubin, 1987) and that findings for students in the *Complete* cohort are generalizable to the *Total* cohort of Black and White students at the C&B/CIRP colleges.

### Science, Mathematics, or Engineering (SME) Graduation as an Outcome Variable

The outcome of primary interest in this study is SME graduation or not (*smegrad*). The coding scheme, descriptive statistics and correlations for this and all other variables is shown in Table 3. Students were judged as SME graduates if they met two criteria: (1) majored in a subject designated as SME, and (2) graduated according to C&B records. If either criterion was not met, the student was judged a non-SME graduate, while those with missing values for either status were coded as missing. Our classification of SME majors follows a consistent research tradition, similar to that outlined by Seymour and Hewitt (1997) and includes computer science and pre- medical and dental studies, but excludes social sciences. See Appendix B for lists and further notes.

Roughly a fifth (19.5%) of the *Complete* cohort graduated with a SME degree. As noted in Table 3, rates for Blacks and Whites were 16% and 20%, respectively. These SME graduation rates differ from those found in various broader samples of colleges: 11.6% of a 1972 nationally representative sample of 2- and 4-year college matriculants (Dunteman et al., 1979)<sup>2</sup>; 17% for a

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<sup>2</sup> Studying a nationally representative cohort of 1972 high school graduates who enrolled in either 2- or 4-year colleges in the fall of that year, Dunteman et al. (1979) found that 13.7% completed a science degree in four years, with another 12.3% “still enrolled” as a science major. When social science majors are not counted among the degree recipients, however, only 6.1% are SME graduates as defined for our study. If the same social sciences proportion holds among those listed as “still enrolled” in science, then 5.5% would be the proportion still enrolled in SME, bringing the total estimated rate of SME persistence for the Dunteman sample to 11.6%.

nationally representative 1985 cohort of 4-year college freshmen (Astin & Astin, 1993); and 16% for a 1990 sample of first-time, full-time, first-year enrollees in 4-year colleges (NSF, 1999)<sup>3</sup>.

The higher rate of the C&B/CIRP cohort is consistent with the high selectivity of these 24 colleges and the empirically established relationship between stronger students and greater likelihood of science interest. In Elliott et al.'s (1995) even more highly selected sample, the rate of SME graduation was 29% (16% for Blacks, 30% for Whites).

### Student-Level Independent Variables

The variable *ethnicity* in this study represents Blacks and Whites and is based primarily on self-report from college applications (Bowen & Bok, 1998), but is supplemented by answers to CIRP ethnicity questions (see Appendix A). Blacks comprise 6.7% of the *Complete* sample ( $n = 1,120$ ). Gender classification was likewise derived from college applications and 54% ( $n = 8,819$ ) of the *Complete* cohort are women. An index of socioeconomic status is not included in these analyses because relevant C&B variables (e.g., self-reported family income, father's and mother's education level) have a high proportion of missing values (51% to 70%; see Appendix A).

Students' scores on the mathematics sub-test of the SAT (*satm*), will serve as indicator for the SME preparation construct. Other theoretically useful indicators, e.g., number of high school science courses taken and grades earned, overall high school GPA, and rank-in-class, are either unavailable or are largely characterized by missing values. Just 30% of all C&B participants, for

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<sup>3</sup> This National Science Foundation report provides two numbers that may be useful in estimating—roughly—a national bench-mark (see Table 2): (1) first-time, full-time, first year enrollees in 4-year colleges in 1990 and (2) number of engineering and natural science degrees awarded in 1995. When numbers for Whites and Blacks are pooled, dividing the number of 1995 degrees by the number of 1990 enrollees yields a SME graduation rate of 16% (9% for Blacks, 17% for Whites). This almost certainly over-estimates the rates, however, as the 1995 degrees could be earned by students beginning in any prior year and at different types of schools under different initial enrollment conditions.

example, have a value for high school class rank. SAT math score, however, is available for more than 96% of students at the 24 CIRP-participating schools (see Appendix A).

Intending to major in SME (*intent*) is our indicator for the SME interest construct. The CIRP questionnaire contained a list of 81 undergraduate majors (including “undecided”) and instructions to “Mark only one oval to indicate your probable field of study” (Higher Education Research Institute, 1989, p. 4). For purposes of this study, responses were dichotomized as either SME or not-SME (see Appendix B for the majors coded as SME). Overall,  $n = 4,583$  (27.6%) of the *Complete* participants are counted as initially intending to major in SME.

#### College-Level Independent Variables

Two college-level variables are used in this analysis. First, the percentage of each college’s 1989 freshman matriculants that within six years graduated with a SME degree (*pctsmc*) is hypothesized as a proxy for the construct “Support for SME.” The median for the 24 CIRP colleges is 20.6%. ( $M = 21.5\%$ ,  $SD = 9$ ). The extent to which this variable relates to specific institutional structures, resources or priorities would be a useful focus of future study, but for the present analyses it at least indexes the proportion of student involvement in SME at the end of their undergraduate careers. Second, the institutional mean *satm* score for students initially planning to major in SME (*smesatm*) is hypothesized as an index of the construct “Competition in SME.” The median is 638 ( $M = 652$ ,  $SD = 43$ ). The high positive correlation between these variables is noteworthy ( $r = .80$ , 95% CI = .59 – .91) and is graphed in Figure 3.

#### Analytical Plan

We will fit a progression of multilevel models ordered by theory and with respect to practical applications. Beginning with *ethnicity* and *gender* reflects not only the relative immutability of these classifications, but also establishes unconditional baseline demographic



relations with respect to SME graduation. This is also roughly comparable to the point at which Bowen and Bok (1998) *concluded* their assessment of ethnic differences in science majors. Intended major (SME or not SME) will be added next, followed by *satm*, as a means of testing Elliott et al.'s (1995) conclusion that demographic differences may be accounted for by differences in interest and preparation. Finally, institutional variables will be added to test the competing hypotheses about the effects of college selectivity.

### Statistical Models

Since our outcome of interest is binary, graduation in SME or not, standard linear regression models are problematic for several reasons: (1) they would predict values outside the 0 to 1 expected range; (2) prediction errors would not be homoscedastic with respect to the regression line; and (3) the distribution of random error scores might not be normal, resulting in biased inferences given normal sampling assumptions. Logit regression addresses these problems by predicting the log-odds of SME graduation, a transformation of the probability that has the property of ratio scaling and a valid range of plus to minus infinity (Hosmer and Lemeshow; 1989; McArdle & Hamagami, 1994; McCullagh and Nelder; 1989). The equation for the logit transformation is written

$$\text{logit}(p) = \ln \left[ \frac{p}{1-p} \right]$$

where  $\ln$  is the natural logarithm,  $p$  is the probability of the event occurring (SME graduation), and  $p/(1-p)$  is the odds that the event will occur. Multilevel logit models, in turn, allow the prediction equation for the logit or log-odds of a student's graduation in SME to vary for each college. The coefficients associated with student-level predictor variables are expressed in terms of the values of the college-level variables of each student's college, and, critically, include unique random effects for each college (Ethington, 1997; McArdle, Paskus, & Boker, in press).

This approach allows partitioning of outcome variance into between- and within-college components, thus accounting for the non-random selection of students into colleges. Following Snijders and Bosker (1999) the random slope multilevel model is written

$$\text{logit}(P_{ij}) = \gamma_0 + \sum_{h=1}^r \gamma_h x_{hij} + U_{0j} + U_{hj} x_{hij}$$

where  $i$  is the  $i$ th student,  $j$  is the  $j$ th college, and  $x_h$  is the  $h$ th predictor variable,  $\gamma_0$  is the intercept log-odds,  $\gamma_h$  represent the  $h$  student-level regression coefficients,  $U_{0j}$  is the random intercept—the variation across colleges in the average log-odds—and  $U_{hj}$  represents variation across colleges in the slopes of the  $h$  predictors ( $x_h$ ). Higher-level predictors, in this case, college-level, can be introduced as modifiers of the  $\gamma$  coefficients. With 24 colleges as the second-level units, a 5% test level (i.e.,  $\alpha = .05$ ) will be highlighted in reports of the multilevel model estimates. Interactions were tested throughout and in most cases only statistically significant findings are reported.

## Results

Results of a sequence of multilevel models are shown in Table 4. The first, model  $M_0$ , with no predictor variables, provides a baseline estimate of the intercept log-odds of SME graduation and of the cross-college variation in this intercept ( $\tau_0^2 = .30, p < .05$ ). The corresponding intraclass correlation ( $\rho_1$ ) of .084 indexes the proportion of variance in SME graduation that is explained by college membership alone. In substantive terms, these statistics indicate the degree of relatedness—non-independence—between students at a given college and the degree to which unilevel models would yield biased results.

Effect-coded variables indexing ethnicity and gender are added in model  $M_1$ . The effect of *ethnicity* is not significant at  $p < .05$ , but the effect of *gender* is significant, with males'

estimated odds of SME graduation twice as high as females' (odds ratio = 1.99). The interaction of *ethnicity* and *gender* was tested and not found significant in this or in subsequent models with student-level predictors. The demographic predictors accounted for a small portion of the cross-college variation in SME graduation, reducing  $\tau_0^2$  to .26 and  $\rho_1$  to .073, and explained 3% of the total variation in SME graduation ( $R^2_{\text{dicho}} = .03$ ; see Table 4). Ninety percent of the still *unexplained* variation is at the student level and 7% is at the college level.

Initial intended major (SME or not) is added in model  $M_2$  and is a strong predictor of SME graduation ( $R^2_{\text{dicho}}$  now .34). SME-intenders, with *ethnicity* and *gender* held constant, are estimated to be more than 17 times as likely as non-SME-intenders to graduate in SME.<sup>4</sup> Of note, taking SME intent into account alters the demographic relations with SME graduation. Figure 4 is a plot of the estimated probability of SME graduation by *intent*, *ethnicity*, and *gender*. With *intent* and *gender* held constant, the effect of *ethnicity* is now significant at  $p < .05$ . This is apparent from the non-overlapping confidence intervals across *ethnicity* within each *gender* and *intent* condition shown in Figure 4. At a given level of intent to major in SME, Whites are estimated 1.8 times as likely as Blacks to graduate in SME. The estimated male advantage, meanwhile, drops to 1.55 from the 1.99 odds advantage estimated by model  $M_1$ . Intended major was found to function similarly across *ethnicity* and *gender*, i.e., interactions of *intent* with each demographic variable, as well as the three-way interaction of *ethnicity* x *gender* x *intent*, were tested and found non-significant here and in subsequent student-level models. The changed demographic relations with respect to SME graduation, however, reflect underlying demographic differences in the likelihood of initially intending SME. Figure 5 is a plot of the estimated probability of initially intending SME as a function of *ethnicity* and *gender*. Black and White

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<sup>4</sup> In contrast, initial intent to major in humanities or in social sciences is much less related to graduation in those fields, odds ratios of 5.3 times and 4.4 times, respectively.

males and Black females, with estimated probabilities of .37, .34 and .33, respectively, do not differ with 99% confidence, but White females, at .21, are significantly less likely to enroll at these schools with expressed intent to major in SME.

SAT math score and the product term, *satm* x *intent*, are added in model M<sub>3</sub> (no other variables interacted significantly with *satm*, i.e., *satm* functioned similarly with respect to SME graduation for men and women, Blacks and Whites). With the demographic variables held constant in this model, there are substantial positive main effects of both intent to major in SME and *satm*, though these effects are slightly attenuated by a negative interaction. That is, for example, the estimated effect of a 50-point increase in *satm* depends on whether or not a student initially intends SME. For students intending SME from the outset, a 50-point higher *satm* is associated with a 1.33 increase in odds of SME graduation. But for those not initially declared in SME, the same *satm* difference has a greater estimated impact, a 1.47 increase in the odds. Overall, including *satm* in the model accounts for another 7% of the total variation in SME graduation ( $R^2_{\text{dicho}} = .41$ ), and for more of the college-level variation, reducing  $\tau_0^2$  to .16 and  $\rho_1$  to .046. Figure 6 is a plot of the SAT math distribution by intended major, *ethnicity* and *gender*. Of import with respect to the first major hypothesis of this study, differences in *satm* fully account for the ethnic differences in SME graduation illustrated in Figure 4, and explain an additional portion of the gender gap. The estimated White/Black odds ratio is no longer different from 1:1 with 95% confidence, and the male/female estimate, though still statistically significant, is now 1.25.

Model M<sub>4</sub> is the last in a sequence testing the effects of the two college-level variables (results of four intervening models are shown in a comprehensive table of multilevel results in

Appendix C)<sup>5</sup>. Models in this sequence tested (1) all cross-level interaction effects of each college level variable (*pctsme* and *smesatm*) with each significant student-level variable in model M<sub>3</sub> (i.e., *gender*, *intent*, *satm* and *intent x satm*) and (2) the random effects of these student-level variables. All non-significant variables, including *ethnicity*, are dropped from Model M<sub>4</sub>. Figure 7 is a path diagram of this final model with notes of the approximate odds ratios estimated for a student initially intending SME. The fixed effects of the student-level variables are little changed from model M<sub>3</sub>. The final log-odds point estimate for *gender* is .19 (male/female odds ratio = 1.21), 2.81 for *intent*, .35 for a 50-point change in *satm*, and -.12 for the interaction of *intent* and a 50 point increment in *satm*. College percentage of SME graduates is positively associated with the intercept log-odds; with other variables constant, log-odds increase .62 per 10 additional percentage points, i.e., 1.9-fold increase in the odds of SME graduation. On the other hand, college mean *satm* among initially SME-intending students is negatively associated with SME graduation; log-odds decrease .53 per 50 point increase in *smesatm*. Small but statistically significant interactions between *smesatm* and (1) *satm* (positive) and (2) the interaction of *intent x satm* (negative) indicate that the effect of *smesatm* varies depending on student intent and SAT math score. For example, model M<sub>4</sub>-generated estimates of the simple effect of a 50-point increase in *smesatm* (with *pctsme* held constant), vary little across *satm* scores for a student initially intending SME (ranging from a .58 odds ratio for a student with *satm* = 550, to a .59 for one with *satm* = 750) but are more variable across the same score range for a student *not* initially intending SME (.42 to .82). In other words, the negative effect of college selectivity was essentially constant across differently scoring students who initially intended SME, but among those not initially indicating SME the negative effect of higher college selectivity was greater for

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<sup>5</sup> The covariance of the intercept and SME-intent slope variance was tested in an additional model and found non-significant.

students with lower scores. Neither college variable interacted with the effect of *gender*.

Variation in the intercepts is still significant at  $p < .05$  ( $\tau_0^2 = .04$ ,  $t = 2.2$ ), but taking the college measures into account has reduced it from .16. Neither the effect of *gender* nor *satm* was found to vary significantly across colleges, but statistically significant variation remains in the effect of intended major ( $\tau_3^2 = .26$ ,  $t = 2.5$ ). That is, there remain differences across colleges in the effect of *intent* that are not accounted for by variables in our model.

Appendix D shows a similar progression of *unilevel* logit models. The estimated coefficients are quite like those of the multilevel models, though the standard errors for the college-level variables are underestimated. One resulting difference between the final models estimated by each approach ( $M_4$  vs.  $LM_6$ ), therefore, is that interaction effects of the college variables with intended major remain significant at  $p < .01$  in the unilevel model, but are not significant at .05 using the multilevel approach. More critically, the unilevel results provide no test for variation of effects at the college level. The final multilevel model,  $M_4$ , indicates that there is still unaccounted for cross-college variation of the intercept log-odds of SME graduation ( $\tau_0^2 = .04$ ,  $t = 2.2$ ), as well as in the functioning of intended major ( $\tau_3^2 = .26$ ,  $t = 2.5$ ).

As estimated by model  $M_4$ , attending a more selective college, defined here as one with a higher mean *satm* among its SME-intending students, is negatively related to SME graduation *if college percentage of SME graduates is held constant*. Such statistical manipulation, however, is unrealistic given the high correlation of these two college characteristics ( $r = .80$ , 95% CI = .59—.91). On average, the higher selectivity schools (at which higher *negative* effects are estimated) are also higher on *pctsmc* (which means higher *positive* effects). A more accurate assessment of the relation between selectivity and odds of SME graduation, therefore, can be made by estimating the model for a given type of student at each college, i.e., using each

college's value of *pctsmc* and *smesatm*. Figure 8 is a plot of such estimates for a SME-intending student with a SAT math score of 550, a score chosen (a) to reflect the kind of relatively less-well prepared student that Elliott et al. (1995) argue would fare better in SME at a less competitive college, and (b) the median score among Black students in this sample initially intending SME. The highest estimated odds for such a student at any of the colleges is 1.0 (corresponding probability = .5), and the 12<sup>th</sup> highest estimate is 0.6. It can be seen in Figure 8 that relatively high estimated odds span the range of selectivity as indexed by *smesatm* along the X axis, and this impression is supported by the non-significant correlation of these odds estimates with *smesatm* ( $r = .01$ ). There is, however, a significant correlation between the estimates and *pctsmc* ( $r = .56$ , 95% CI = .20 — .79).

Another approach to understanding the SME prospects of relatively less-well prepared students at these colleges is represented in Figure 9. Here the *empirically* observed odds of SME graduation are plotted for students at each college who initially intended SME and had a SAT math score in the range of 500 to 590. The  $n$  of these college subsamples ranges from 4 to 237 (8 to 154 for the twelve colleges with observed odds in the top half). These empirical odds do not correlate significantly with *smesatm* or *pctsmc*, nor do they correlate with the odds estimated by model M<sub>4</sub>. In other words, actual SME outcomes for these relatively low-scoring students who intended SME were not related to either of the college variables in this study, nor to the odds estimated by our final model for a SME-intending student in the middle of this SATM range. A similar lack of significant relation was found between the college variables and empirical odds for SME-intenders with *satm* in the 600s at each college<sup>6</sup>. This analysis underscores the idea that

<sup>6</sup> These odds did correlate significantly, however, with those estimated by model M<sub>4</sub> ( $r = .57$ , 95% CI = .22— .79). This is not surprising given that students with *satm* in the 600s constitute 41% of the SME-intending students in this sample, compared with the 20% constituted by those in the 500s, and the 34% by those with scores  $\geq 700$ . The estimated model parameters are driven more by the larger numbers of students whose scores are in the 600s.

prospective students hoping to gauge their chances of success in SME at these colleges cannot do so by simply considering a college's relative mean SAT math score, percentage of SME graduates, or combination of the two, but may be helped by knowing specific probabilities of success at each college for students with scores like theirs. That is, in the case of a student with a score in the 500s, comparing the odds shown in Figure 9 may be the best guide, though ideally qualified by knowledge of the sample size. The school with the highest empirical odds (3.5), for example, had a sample size of nine SME-intending students with *satm* in the 500s.

### Discussion

This study presents statistical models of science, math or engineering (SME) graduation for  $n = 16,616$  Black and non-Hispanic White students who began at 24 selective colleges in the fall of 1989. The data were collected by The Andrew W. Mellon Foundation and are part of the “College and Beyond” (C&B) data set. Graduation with a SME major within six years of matriculation was the outcome of primary interest. Predictor variables at the student level included (1) ethnicity (Black or White), (2) gender, (3) intending—or not—a SME major at the start of freshman year, and (4) SAT math score (SATM), while college-level predictors were (1) percentage of the entering class graduating in SME, and (2) mean SATM of students intending SME. The colleges in the sample are mostly highly selective, so generalization of our findings to the population of *all* college matriculants is unwarranted. Evidence suggests that the processes of sample selection here are related to SME graduation, and regression estimates, therefore, are likely to be biased with respect to the overall college-bound population. Within the limits of this sample, however, the multilevel analytic approach we used accounts for the biases that would otherwise result from the non-random grouping of students at these colleges. The major hypotheses to be tested were (1) that the disproportionate attrition of Black students and female



students from SME majors at selective colleges can be accounted for by differences in pre-college measures of mathematical competence and (2) that with math ability and science interest held constant, attendance at more selective colleges is negatively related to SME persistence.

The first hypothesis was fully supported with respect to Black/White differences in SME persistence, and partially supported with respect to gender differences. Among those intending SME at the outset of freshman year, 40% of Blacks and 56% of Whites graduated with a SME degree. When science was *not* the area initially intended, Whites were also more likely than Blacks to graduate in SME (6.3% vs. 4%). These differences, which correspond to a 1.8 times greater likelihood of SME graduation for White than Black students of comparable initial intent, were accounted for by differences in SAT math scores. Among both initial SME-intenders and non-intenders, the scores of Whites averaged more than a *SD* higher than those of Blacks. When conditioned on SAT math score, the baseline 1.8 White/Black odds of SME graduation ratio was reduced, with 95% confidence, to a ratio not different from equal odds, i.e., 1.0. The same trend was found for the male/female odds of SME graduation ratios. With ethnicity and intent held constant, men were 1.55 times as likely as women to graduate in SME, but when SAT math scores were taken into account, the estimated male advantage was cut to 1.25 (women averaged about half a *SD* below men on the SAT math). It is noteworthy that tests of interaction effects of SAT math scores with both ethnicity and gender were conducted and found non-significant. That is, SAT math scores were found to function similarly with respect to SME graduation for men and women, Blacks and Whites.

The second hypothesis, that relatively less-well academically prepared students who intend a SME major would fare better at less selective colleges, was less clearly supported. We found a negative effect of selectivity, as indexed by mean SAT math score among SME-

intending students, but this tended to be offset by a positive effect related to percentage of graduates in SME, a variable highly positively correlated with selectivity. On average in this sample, then, the negative effect of mean SATM was counterbalanced by the positive effect of percentage of SME graduates, with a net result that college selectivity did not correlate with the probability of SME graduation after differences on student-level variables were accounted for. Our findings likewise fail to support the opposite hypothesis, an extension of Bowen and Bok's (1998) overall argument, that higher-selectivity schools would boost the likelihood of SME graduation for students of given interest and preparation.

There are shortcomings of these data, however, that militate against adequately evaluating the effect of college selectivity. One is the restricted selectivity range of these colleges; they are disproportionately comprised of highly selective institutions and the *SD* of their mean SAT math scores is only 41 points. Another is that the SAT math score was the only available student variable relevant to math and science preparation. Using the statistical model, this variable was held constant for students at different colleges, but this does not account for possible college-related differences on other indicators of readiness for academic success, some of which are typically found on college applications. Only 6% of the SME-intending students in the most selective third of these colleges had SAT math scores in the 500s, compared with 34% in the least selective third. Despite their comparable SAT math scores, it would be unfounded to assume that those included in the smaller fraction selected by and attending the top tier schools have "the same" academic potential as the proportionally larger group of students in the bottom tier.

The confounding possibilities of such "selection effects" were emphasized by Pascarella and Terenzini (1991) in their review of literature on effects of college. A reasonable hypothesis

is that the low-scoring SME-intending students at the most selective colleges in this sample impressed admission officials with *other* characteristics, and that such students would, on average, be rated more highly on such characteristics than the comparably SAT-scoring students at the less selective colleges. If this hypothesis is true, then our *de facto* null result with respect to the effect of college selectivity has different implications for the strength of the Bowen and Bok (1998) and Elliott et al. (1995) hypotheses. If indeed the students with SATM in the 500s at the more selective schools had greater potential than those at the less selective ones, then hypothesizing a positive association of SME graduation with college selectivity (following Bowen and Bok) is logical. Under such conditions, however, a positive finding might be explained by measures of the *student* differences, without recourse to college differences. Since we did not find a positive net effect of selectivity, it is compelling to speculate either that (a) scorers in the 500s at the high-tier colleges really were not much differently prepared than the scorers in the 500s at the low-tier ones, or (b), if they *were* better prepared, that something about the high-tier colleges' environments had an inhibitory effect on these students' SME success. In either case, with respect to SME graduation, there is little to support the Bowen and Bok idea that the more selective schools in this sample were adding value. On the other hand, if the high-tier college 500s-scorers actually had greater SME potential, then our null result would not be inconsistent with the Elliott et al. hypothesis. If such students had enrolled at the low-tier schools a reasonable hypothesis is that they would have graduated in SME at a higher rate than they did at the high-tier schools. However, without random assignment of students to colleges of different selectivity, testing this hypothesis is difficult if not impossible.

Intention to major in SME at the outset of freshman year is by far the most powerful of the predictors used in these models. This may seem like an obvious conclusion, but it is

noteworthy because SME intent was much more strongly related to SME graduation than were comparable intent-graduation relations among those intending humanities or social sciences. The key to the difference is in the behavior of *non*-SME intenders; very few of such students (6%) graduated as a science major, compared with 18% of non-humanities intenders who graduated in humanities, and 22% of the non-social science intenders who graduated in social science. Consistent with much of the SME-persistence literature, Blacks in this sample of selective college freshmen were more likely than Whites to express intent to major in SME. Most of this disparity in intentions, however, was driven by the very low rate among White females. Black males' rate of SME intent (37%) was not significantly different from either White males' or Black females' (34 and 33%, respectively), but White females' rate was much lower (21%). With SAT math score held constant, however, estimated ethnic differences in the likelihood of intending SME increased among students of each gender: comparably-scoring Black men were nearly twice as likely as White men to intend a SME major, while Black women were more than three times as likely as White women to do so. Thus, with SAT math scores held constant statistically, Blacks were much more likely than Whites to aspire to science at these colleges. The higher average rate of SME intent among these Black students explains why the overall ethnic difference in percentage earning a SME degree (16% of all Blacks in this sample, compared with 20% of Whites) is less than the ethnic differences found among those of equivalent intent.

The multilevel logit models emphasized here, while yielding fixed effect estimates largely similar to those of a traditional unilevel approach, allowed for the specific recognition that there is still-*unexplained variation* across colleges in the functional relationship between intended major and SME graduation. This is different from finding a systematic *interaction*

between college characteristics and intended major; such a finding emerged significant at  $p < .01$  from the unilevel models, given the unrealistically small standard errors, but dropped from the multilevel model.

### Implications

The National Science Board (2002) reiterated recently that fostering minority and female interest in science majors should be a national priority:

“Whether women and minorities are attracted to S&E majors is also of national interest because together they make up the majority of the labor force, and they have traditionally not earned S&E degrees at the same rate as the male majority. Their successful completion of S&E degrees will determine whether there will be an adequate number of entrants into the S&E workforce in the United States” (Chap. 2, p. 3).

Our analyses suggest that Black students entering these selective colleges were not lacking in interest—at least insofar as self-reported intent to major in SME indexes interest—but that White women were. A similar pattern held for a nationally representative sample of students graduating from high school in 1992 (National Center for Education Statistics, 2000). Understanding this gender gap among Whites in development of pre-college science interest may have significant implications for U.S. science productivity. Among high ability science students (SATM > 650), Seymour and Hewitt (1997) found that “inappropriate reasons” for initially choosing a SME major were far more likely to play a role in attrition for non-Whites (35%) than for Whites (6%). The “active influence of others,” they reported, including SME recruitment efforts, was more often cited as an inappropriate reason for initial choice of science by ethnic minority and female students who left science: “Some students clearly had been encouraged to enter majors for which they had insufficient interest, preparation or understanding” (p. 324). This qualitative evidence may be related to our finding that among students with similar SAT math scores, Blacks were substantially more likely than Whites to initially declare a SME major. Research is needed to

establish more precise indicators of SME intent and motivation, e.g., ones that differentiate between theoretically relevant constructs like perceived competence, and intrinsic and extrinsic interest (e.g., Dweck & Leggett, 1988; Deci & Ryan, 1991). Such measures would allow admission officials to make more nuanced judgments about the strength of SME interest, and might account for the unexplained variation across colleges that we found in the functional relation between initially intending and completing a SME major. In their book on assessing talent in the context of college admission decisions, Wing and Wallach (1971) emphasize the utility of identifying intrinsic interest, like that of “the student whose skill at scientific pursuits has been indicated by his winning recognition in science contests for projects that he carried out in his basement laboratory” (p. 22). They argue that accomplishments arising from “spontaneous inclinations on his part more than because of the kinds of extrinsic pressures from school and from parents that could lead to aspiring to higher grades” are a more telling harbinger of accomplishments to come.

The findings of our study with respect to ethnicity replicate those of the other quantitative studies reviewed and suggest that differences in SME graduation rates between Blacks and Whites at selective colleges are related to differences in pre-college mathematics preparation. At the national level, e.g., among all SAT test-takers, the large mean differences in admission test scores across ethnic groups reflect a myriad of unequal social and economic conditions that bear on educational opportunity. Within these selective colleges, however, test score differences by ethnic group are primarily related to differentially weighting ethnicity in admission decisions (as suggested by the subtitle of Bowen and Bok’s (1998) analyses, *Long-Term Consequences of Considering Race in College and University Admissions*). Ethnic differences in aggregate test scores at these colleges could be substantially reduced—though so would disadvantaged

students' representation on such campuses—if admission decisions were made with respect only to academic criteria such as high school curriculum, grades, and standardized test scores. Because students also make choices among institutions, a college's admission criteria will not precisely shape the entering class and within-college demographic differences in qualifications reflecting students' preferences could still emerge. But a large gap between the SAT math scores of the average Black and White student intending SME is typical of the colleges in this sample (median difference = 120 points favoring Whites,  $M = 118$ ,  $SD = 42$ ) and suggests that ethnicity plays a similar role in admission decisions across these institutions. To the extent that the admission process is related to the observed ethnic differences in SAT math scores, our analyses suggest it is also related to the ethnic differences in SME graduation rates.

SAT math scores also accounted for a substantial portion of the gender difference in SME graduation among students of comparable intent, but a small effect of gender persisted in our final model (men estimated 1.2 times as likely as women). As discussed earlier in the context of the effect of college selectivity, there are many possible unmeasured academic and motivation variables on which the men and women in this sample may differ. The nature of the high school math and science curriculum, grades earned in these courses, and “reasons” for the goal of a science degree are just a few of those suggested by the literature. Study of the formation and functioning of men and women's differing science-related goals, interests and preparation should be ongoing. A key finding of this study is that intended major and math preparation functioned similarly in this sample to predict SME graduation for men and women. The 2:1 overall male advantage in SME graduation was mostly explained by the lower likelihood of White females to initially intend a SME major, and by the male advantage, among both Blacks and Whites, in SAT math scores. Again, the admission process is related to the difference in SME graduation

rates between similarly interested male and female students to the extent that differences in SAT math scores between those *admitted* are associated with the score differences between those *enrolling*.

More study of the mechanisms underlying SAT math scores as an explanation of variation in science persistence at such colleges would be useful. Are students with lower scores more likely to have cultivated interests in other fields, which then are better primed for stimulation in college? Do they place less value on the science degree? Or are their lower scores related to discouraging relatively lower grades in early quantitative courses? Whatever the mechanisms, SAT math scores were similarly positively associated with SME graduation for Blacks and Whites, men and women, initial SME- and non-SME-intending students, and across colleges. This finding has implications for college admission decision-makers and for efforts to improve pre-college math and science preparation for all students. But it should not be interpreted to mean that when choosing between two science-interested students, the one with the higher math SAT *always* ought to be selected; as admission officers well know, “other factors” usually are not “equal.” Evidence of particularly strong intrinsic motivation to study science, for instance, may suggest that the lower-scoring student is more likely to succeed. The statistical findings indicate, rather, that increases in math SAT scores can be expected, *on average*, to be associated with higher likelihood of science persistence, regardless of ethnicity or gender. Thus, to the extent that standardized mathematics test scores are *systematically* discounted when considering students from particular groups, whether ethnic minorities, alumni children, or recruited athletes, SME graduation rates of the students in such groups are likely to be lower than those of students whose scores are not discounted. An important direction for further research would be to investigate possible social psychological and intergroup perception effects related to



such group differences in SME persistence. For example, Whites initially intending a SME major in this sample were 1.8 times more likely than comparably intending Blacks to achieve their goal. Are students at selective colleges aware of such differences? If so, what attributions do they make about the cause of such differences and do these attributions differ by demographic group? Are the perceptions and attributions related to changes in stereotyping, whether of self or others, or in attitudes about institutional climate and race relations?

Elliott and his colleagues (1995) concluded that race-sensitive admission, while increasing access to elite colleges, was inadvertently causing disproportionate loss of talented underrepresented minority students from science majors. For students of comparable interest and ability, they expect greater likelihood of graduation in science at a less selective college. Bowen and Bok (1998) reached the opposite conclusion, claiming a positive effect of selectivity on overall chances of graduation. Resolving these apparently conflicting views with respect to science majors has important implications for the prospects of some of the most able underrepresented minority students in the United States. We found no support for the idea that chances of graduating with a science degree are improved by attending a more selective college. Our findings are more consistent with the Elliott et al. hypothesis, but research designed specifically to study these questions is necessary. In addition to more proximal measures of institutional science environments, such research should include multiple and repeated measures of students' scientific interest, motivation and relevant academic preparation, and of the subjective utilities students assign to graduating from a more prestigious institution vs. graduating with a science degree. Elliott et al. write,

...non-Asian minority students initially aspiring to science will continue for some time to bear a cost in altered academic and vocational goals. It may well be a cost such students regard as worth bearing in return for benefits in quality of education, variety of points of view, richness of social experience, prestige of degree, or enhancement of career

prospects. Still, it is a serious cost, it ought to be acknowledged as such, and if possible minimized (p. 35).

Prospective science students' awareness of the possibility and risk of such a tradeoff, regardless of ethnicity or gender, might be increased if colleges publicize specific information about the SME graduation rates of students with different pre-college academic qualifications. We suggest that a student interested in science try to answer this question for each college under consideration: How do students with interests and academic preparations *like mine* do in science? Our analyses indicate that simpler choice strategies, whether for the least or most selective school in the set, or the one with the highest percentage of SME graduates, would be ineffective. Even a more complicated search for optimal combinations of lower selectivity with higher percentage of SME graduates, as suggested by our statistical model (see Figure 8), would not yield the best choice for every student. As illustrated in Figure 9, actual graduation rates of students with SAT math scores in the 500s are different from (and do not correlate with) the predictions made by the statistical model. Admission officials and college counselors can help students aspiring to science by gathering and publicizing detailed profiles of the trajectories of students with science interest but different levels of preparation, including standardized test scores, at particular colleges. Such data may lead to improved decision-making by prospective science students as well as by institutional officials.

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## Appendix A

### Technical Notes

#### Incomplete Data Analyses

To more formally assess the degree to which sample attrition is related to variables of interest in this study, CIRP participation (yes or no) was logit-regressed on the available variables of ethnicity, gender, SAT math score and SME graduation status. Together, these predictors accounted for less than 1% of the variance in CIRP participation. It was also found that adding CIRP participation to a logit model with ethnicity, gender and SAT math score as predictors of SME graduation (the primary outcome of interest in this study) made no improvement in the prediction. Given these small relations between CIRP participation and variables of theoretical interest, additional statistical techniques to account for any biases will prove ineffective.

#### Ethnic Classification

Among participants from the 24 colleges that participated in CIRP,  $n = 445$  (1.6%) were classified as “unknown” on the C&B ethnicity variable, INSTETH. The CIRP survey had seven ethnic classifications and participants were instructed to “Mark all that apply.” Any C&B “unknowns” who selected just one of the CIRP ethnicity options (as opposed to multiple-categories) were classified on our *ethnicity* variable according to this single CIRP choice. This process resulted in reclassification for 184 of the C&B unknowns: 6 as Black, 1 Hispanic, 20 Asian, 1 Native American, 132 White, and 1 as “other.”

#### Socioeconomic Status (SES)

Analyzing relations among C&B students with complete data on a composite SES indicator, Bowen and Bok (1998) reported an “imperceptible effect” of SES, reducing “by only about 1 percentile point” the large gap between Blacks and Whites in college percentile rank in class (p.



80). Bowen and Bok further suggest that the SES measures at their disposal in the C&B data set were crude, providing "...a very imperfect proxy for the factors that matter the most."

### Imputing *satm* Scores

The primary source for this variable was C&B data from college applications (SATMATH). For those without it, but who had a self-reported SAT math score on the CIRP survey ( $n = 50$ ), the latter was used to impute a score on *satm*. A total of  $n = 14,574$  students at the 24 C&B/CIRP schools had both an application-based (C&B) SAT math score and a self-reported score from the CIRP. Regression of the C&B score on the CIRP score yielded  $R^2 = .87$  and the following equation:

$$\text{C\&B SATM} = 45.26060463 + .92818662(\text{CIRP SATM})$$

This equation was used to impute *satm* for  $n = 50$  students who were missing a score on the C&B variable SATMATH. Thus, for example, the imputed *satm* score for a student with CIRP SATM = 600 was 602.

### Graduation Status

Values of the C&B variable GRADSTAT were used to assign graduation status. Students classified as "Graduated," i.e., completed a degree at the C&B school of entry within six years ( $n = 20,782$  or 85%), and the relative few listed as "Active, still on the rolls," ( $n = 53$  or 0.2%) were credited with valid graduation statuses in this study. Students who were expelled for any reason, who withdrew, or who failed to graduate for unknown reasons were all counted as *smegrad* = "No." Those missing a GRADSTAT classification ( $n = 220$ ) were counted as missing (not "No") for *smegrad*. Nine participants listed as "Deceased" were also classified as missing for *smegrad*. Of course, it is probable that some of those missing a graduation status left their C&B institution of initial matriculation and went elsewhere to obtain a SME degree. Tracing those paths, however, is

beyond the capacity of the C&B data (a follow-up survey, Bowen & Bok, 1998, of a sample of C&B matriculants, some of whom graduated from other colleges, had no question about academic major). Additionally, the practical focus of this study is predicting success in a given field at the selective institution of initial entry.

### Maximum Rescaled $R^2$

As noted in the SAS Online documentation for Version 8 (SAS Institute Inc., 2000), this index is a rescaling (proposed by Nagelkerke, 1991) of the “Cox and Snell” generalization of the

coefficient of determination,  $R^2 = 1 - \left\{ \frac{L(0)}{L(A)} \right\}^{\frac{2}{n}}$ , by its maximum possible likelihood,

$R^2_{\max} = 1 - \left\{ L(0) \right\}^{\frac{2}{n}}$ , where  $L(0)$  is the intercept-only baseline model and  $L(A)$  is an alternative model.

### Weighting the Sampled Cases for use in the SAS NLMIXED Program

The C&B dataset contains records of all entering freshman at 22 of the 24 CIRP institutions, but sampling procedures were used at the remaining two. Specifically, White students were sampled (*all* Black students’ records were included) and the INSTWT variable reflects the inverse of the probability of their inclusion (Bowen & Bok, 1998). Our *Complete* sample includes 1,025 records sampled from one institution (INSTWT=1.6099887767) and 1,118 from the other (INSTWT=2.0429447853). It was not apparent in the SAS documentation for PROC NLMIXED (SAS Institute, 2000), however, that a built-in function for weighting the data was available. The SAS code below demonstrates the procedure we used to approximate the weighting specified by the C&B sampling design. It randomly samples—with replacement—cases from among the C&B weighted cases the number of times necessary to equal the  $n$  of the INSTWT-weighted sample at

each of the two institutions (as determined, for example, by using PROC FREQ with the “WEIGHT instwt” command).

```

/* FIRST CREATE A DATA SET WITHOUT THE SAMPLED CASES */
DATA noweights;
  SET complete;
  IF instwt NE 1 THEN DELETE;
RUN;

/* NOW SELECT ONLY THE UNIVERSITY XX SAMPLING STUDENTS,
   ALL OF WHOM HAVE A WEIGHT OF 2.0429447853, N = 1118 */

DATA sampled;
  SET complete;
  IF instwt < 2 OR instwt > 2.1 THEN DELETE;
RUN;

/* NOW RANDOMLY SAMPLE (WITH REPLACEMENT) 2,284 TIMES
   FROM THE CASES WITH INSTWT=2.0429447853, THUS EQUALING
   THE NUMBER CREATED BY THE 'INSTWT' WEIGHTING (see SAS
   Language and Procedures: Usage 2, p. 235) */

DATA sampled;
  choice=INT(RANUNI(8689)*n)+1;
  SET sampled POINT=choice NOBS=n;
  i+1;
  IF i > 2284 THEN STOP;
RUN;

/* NOW ADD THE SAMPLED CASES TO THE UNWEIGHTED CASES
   (see SAS Procedures Guide, Version 6, 3rd Ed., p. 43) */

PROC APPEND BASE = noweights DATA = sampled;
RUN;

```

When the following unilevel model (and others) was fit to the resulting sample, estimated parameters and standard errors were approximately equal to those obtained using the INSTWT variable with the *Complete* cohort.

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```

PROC LOGISTIC DATA = noweightS DESCENDING;
TITLE 'Model SMEGrad vs. NOT';
TITLE2 'INTENT + SATM50 + PCTSME + SMESATM';
TITLE3 'DATA = noweightS';
MODEL smegrad = intent satm pctsme smesatm
/CTABLE PPROB=.195 CLPARG=WALD CLODDS=PL RSQUARE;
RUN;

```

### Sample of SAS NLMIXED Program

The following is the code used to fit Model M<sub>4</sub>:

```

PROC NLMIXED QMAX=100 DATA = complete;
TITLE 'smegrad = gender + intent + SATM + Two College-Level';
TITLE2 'Drop Ethnicity and pctsme->intent';
TITLE3 'Random Intercept and Slope for Intent (Cov Fixed to Zero)';
TITLE4 'DATA = complete';

PARMS mb00=-1.4 mb01=.7 mb02=-.6 mb20=.19 mb40=2.84
      mb80=.36 mb82=.09
      mb110=-.1 mb112=-.16
      vu0=.04
      cu04=0 vu4=.24
      ;
b0 = mb00 + (mb01*pctsme) + (mb02*smesatm) + u0;
b2 = mb20 ;
b4 = mb40 + u4;
b8 = mb80 + (mb82*smesatm);
b11 = mb110 + (mb112*smesatm);

logodds = b0 + (b2*gender) + (b4*intent) +
          (b8*satm) + (b11*intentXsatm);
odds = EXP(logodds);
prob = odds/(1+odds);

MODEL smegrad ~ BINARY (prob);
RANDOM u0 u4 ~ NORMAL([0,0],
[vu0,
0, vu4])
SUBJECT=institution;
PREDICT prob OUT=predict;
RUN;

```

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SAS Code for Variance of the linear predictor ( $\sigma^2_F$ ). (see Snijders & Bosker (1999), p.225)

```
*****/
CALCULATE VARIANCE OF LINEAR PREDICTOR, i.e., OF THE FIXED
ESTIMATE OF THE LOG-ODDS, FOR MODEL 1
*****/
```

```
DATA logodds;
  SET complete;
      b0 = -1.5104;
      b1 =  0.1672;
      b2 =  0.6929;
  logodds = b0 + (b1*ethnicity) + (b2*gender);
  PROC UNIVARIATE;
    VAR logodds;
RUN;
```

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## Appendix B

## Science, Mathematics and Engineering Classification

Table B1 shows the majors classified as SME in this study. Exclusion of the social sciences is argued for by Astin and Astin (1993) based on their findings about the trajectories of students *initially* interested in psychology or other social science majors. Though roughly half ended up leaving the social science area, less than 2% move into a traditional SME discipline. Furthermore, those who initially indicated intent to major in something other than either SME or social science (e.g., humanities) were more likely to switch into a traditional SME field (5.5%) than were the initial social science aspirants. Astin and Astin also found that the multiple  $R$  obtained from regression equations predicting SME persistence fell substantially when social science fields were included with natural science and engineering majors in the definition of SME. Hilton, Hsia, Solorzano and Benton (1989) studied "...high-ability minority students who intended to enroll in college and to major in mathematics, science, engineering or premedical fields" (p. 1) and characterized as "a nontrivial task" the operationalization of specific majors. With guidance from NSF's Committee on Equal Opportunities in Science and Engineering, they, too, excluded psychology and other social sciences.

A few C&B final majors were questionable with respect to SME classification. In most cases, the classification of *intended* majors on the CIRP survey was used to position them: *Agriculture* was classified among "OTHER FIELDS," *Audiology, Nursing and Health Sciences* were counted as "PROFESSIONAL." Exceptions to this rule included *Pre-Med, Dentistry, Computers, and Computer & Information Sciences*, which CIRP classified as either PROFESSIONAL or OTHER, but for reasons of congruence with most other SME literature, were classified as SME for this study.

Table B1

Majors Classified as SME for this Study"College & Beyond" Majors indicated on Transcripts

Biological Sciences	Mathematics
Pre-Med	Astronomy, Atmospheric Sciences
Dentistry	Chemistry
Computers	Geology
Material Sciences	Geological Sciences
Mechanical Engineering	Physics
Engineering	Other Physical Sciences
Computer and Information Sciences	

Intended Majors Reported on CIRP Survey

<p><b>BIOLOGICAL SCIENCE</b></p> <p>Biology (general)</p> <p>Biochemistry or Biophysics</p> <p>Botany</p> <p>Marine (Life) Sciences</p> <p>Microbiology or Bacteriology</p> <p>Zoology</p> <p>Other</p>	<p><b>PHYSICAL SCIENCE</b></p> <p>Astronomy</p> <p>Atmospheric (incl. Meteorology)</p> <p>Chemistry</p> <p>Earth Science</p> <p>Marine (incl. Oceanography)</p> <p>Mathematics</p> <p>Physics</p> <p>Statistics</p> <p>Other</p>
<p><b>ENGINEERING</b></p> <p>Aeronautical or Astronautical</p> <p>Civil</p> <p>Chemical</p> <p>Electrical or Electronic</p> <p>Industrial</p> <p>Mechanical</p> <p>Other</p>	<p><b>PROFESSIONAL</b></p> <p>Pre-dental, Pre-med, Pre-vet</p>
<p><b>TECHNICAL</b></p> <p>Data Processing or Computer Programming</p>	<p><b>OTHER FIELDS</b></p> <p>Computer Science</p>

Full Sequence of Multilevel Models for the Prediction of College Science, Math or Engineering Graduation.  
 Results of Models M4-M7 were not shown in Table 4. Model M8 here is the same as Model M4 in Table 4.

Parameter	M0	M1	M2	M3	M4	M5	M6	M7	M8
<b>Fixed Effect (Level 1)</b>									
Intercept	-1.46 (13)	-1.51 (13)	-1.47 (13)	-1.20 (12)	-1.39 (19)	-1.37 (19)	-1.39 (19)	-1.37 (19)	-1.40 (25)
<i>ethnicity</i>		.17 (1.9)	.58 (6)	-.03 (0.3)	-.05 (0.5)	-.06 (0.5)	-.10 (0.9)	-.09 (0.8)	
<i>gender</i>		.69 (17)	.44 (9)	.22 (4)	.24 (4)	.21 (4)	.13 (1.7)	.19 (4)	.19 (4)
<i>intent</i>			2.87 (57)	2.79 (55)	2.99 (43)	2.94 (45)	2.90 (23)	2.89 (23)	2.81 (22)
<i>satm</i>				.34 (18)	.38 (16)	.36 (18)	.35 (12)	.36 (18)	.35 (18)
( <i>satm</i> x <i>intent</i> )				-.10 (3)	-.17 (4)	-.12 (3)	-.13 (3)	-.11 (3)	-.12 (3)
<b>Fixed Effect (Level 2)</b>									
<i>pctsmc</i> ->Intercept					.74 (7)	.68 (7)	.69 (7)	.63 (6)	.62 (6)
<i>smesatm</i> ->Intercept					-.63 (6)	-.58 (5)	-.60 (6)	-.54 (5)	-.53 (5)
<i>pctsmc</i> -> <i>gender</i>					-.16 (1.3)				
<i>smesatm</i> -> <i>gender</i>					.00 (0.0)				
<i>pctsmc</i> -> <i>intent</i>					-.49 (4)	-.38 (3)	-.48 (2.2)	-.46 (2.1)	
<i>smesatm</i> -> <i>intent</i>					.44 (3)	.33 (3)	.39 (1.7)	.36 (1.6)	
<i>pctsmc</i> -> <i>satm</i>					-.08 (1.7)				
<i>smesatm</i> -> <i>satm</i>					.16 (4)	.08 (4)	.10 (3)	.09 (4)	.09 (4)
<i>pctsmc</i> ->(intent x <i>satm</i> )					.15 (1.8)				
<i>smesatm</i> ->(intent x <i>satm</i> )					-.27 (3)	-.13 (3)	-.17 (4)	-.16 (4)	-.16 (4)
<b>Random Effect</b>									
Intercept Variance	$\tau_0^2$	.30 (3.2)	.26 (3.2)	.23 (3.1)	.16 (3.0)	.04 (2.1)	.03 (2.0)	.04 (2.2)	.04 (2.2)
Slope Variance of <i>gender</i>	$\tau_2^2$						.06 (1.8)		
Slope Variance of <i>intent</i>	$\tau_3^2$						.21 (2.5)	.21 (2.5)	.26 (2.5)
Slope Variance of <i>satm</i>	$\tau_4^2$						.01 (1.5)		

Table continues



Parameter	M0	M1	M2	M3	M4	M5	M6	M7	M8
<u>Goodness-of-Fit</u>									
Deviance (-2 LogLikelihood)	15910	15621	11580	11242	11171	11183	11119	11142	11147
A -2LL	0	289	4330	4668	4739	4727	4791	4768	4763
<u>Intraclass Correlation</u>	$\rho_1$	.084	.073	.065	.046	.012	.009	.012	.012
Variance of the linear predictor	$\sigma^2_F$	.12	1.78	2.35	2.60	2.49	2.34	2.36	2.33
Total Variance of <i>smegrad</i>	<i>varY</i>	3.67	5.30	5.80	5.93	5.82	5.66	5.69	5.66
Proportion Explained Variance	$R^2_{dicho}$	.03	.34	.41	.44	.43	.41	.41	.41
Prop Unexplained at Level 1	<i>UL1</i>	.90	.62	.57	.55	.57	.58	.58	.58
Prop Unexplained at Level 2	<i>UL2</i>	.07	.04	.02	<.01	<.01	<.01	<.01	<.01

Note. All models were fit with SAS PROC NLMIXED with  $N = 16,616$ , and  $C(\text{colleges})=24$ ; Coefficients shown in bold type are significant at  $p < .05$ .

MLE (ln) parameter estimates are listed with approximate  $t = p/se(p)$  in parentheses. *smesatm*, the mean institutional SATM score among SME-intending students, and *satm* are each centered about the grand median among students intending SME (650) and scaled to represent an increment of 50 SATM points. *pcisme* = the percentage of a college's matriculants who graduated in SME, centered around the approximate grand median of 20% and scaled to represent 10 percentage point increments.

Following Snijders & Bosker (1999),  $\sigma^2_F =$  observed variance of estimated log-odds (see Appendix A).  $\sigma^2_R$  (Level 1 residual variance) =  $\pi^2/3 = 3.29$ .  
 $\rho_1 = t_0^2/(t_0^2 + \sigma^2_R)$ ;  $varY = \sigma^2_F + t_{02} + p^2/3$ ;  $R^2_{dicho} = \sigma^2_F / varY$ ;  $UL1 = \sigma^2_R / varY$ ;  $UL2 = t_0^2 / varY$ .

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Unilevel Logit Models of SME Graduation as a Function of Student-Level Variables

Model	Variable	Parameter estimates				Odds Ratio	99% Wald Conf Limits		Fit indices			
		$B_k$	$t$	$X^2$			LRT	$R^2$ *	ACC			
LM <sub>0</sub>	Intercept	-1.42		5,256					0*			
LM <sub>1</sub>	Intercept	-1.50	(38)	1,267					346	.03	58.5%	
	Ethnicity	.16	(2)	4		1.2	.94	1.46				
	Gender	.73	(18)	331		2.1	1.87	2.30				
LM <sub>2</sub>	Intercept	-1.51	(30)	970					4580	.38	82.9%	
	Ethnicity	.53	(5)	31		1.7	1.33	2.18				
	Gender	.46	(9)	95		1.6	1.40	1.79				
	Intent	2.85	(57)	3,456		17.3	15.27	19.60				
LM <sub>3</sub>	Intercept	-1.20	(24)	536					5012	.42	82.7%	
	Ethnicity	-.03	(0.3)	0		1.0	0.74	1.26				
	Gender	.21	(4)	19		1.2	1.09	1.41				
	Intent	2.77	(55)	3,138		15.9	13.99	18.04				
	SATM	.33	(17)	393		1.4	1.34	1.46				
	SATM*Intent	-.10	(3)	10		0.9	0.84	0.98				

Table continues

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Model	Variable	Parameter estimates				Odds Ratio	99% Wald Conf Limits		Fit indices		
		$B_k$	$t$	$X^2$			Ratio	Lower	Upper	LRT	$R^2$
LM <sub>4</sub>	Intercept	-1.41	(24)	604					5184	.43	81.8%
	Ethnicity	-.04	(0.4)	0		1.0	0.73	1.26			
	Gender	.22	(4)	15		1.3	1.08	1.45			
	Intent	2.96	(42)	1,895		19	16.26	23.09			
	SATM	.38	(19)	269		1.5	1.38	1.56			
	SATM*Intent	-.18	(5)	15		0.8	0.75	0.94			
	PCTSME	.72	(10)	122		2.1	1.74	2.44			
	SMESATM	-.62	(9)	87		0.5	0.45	0.64			
	PCTSME*Gender	-.15	(1.3)	2		0.9	0.63	1.16			
	SMESATM*Gender	.01	(0.1)	0		1.0	0.75	1.35			
	PCTSME*Intent	-.53	(4)	16		0.6	0.42	0.83			
	SMESATM*Intent	.48	(4)	13		1.6	1.15	2.29			
	PCTSME*SATM	-.09	(2.3)	5		0.9	0.82	1.02			
	SMESATM*SATM	.16	(4)	16		1.2	1.06	1.31			
LM <sub>5</sub>	PCTSME*Intent*SATM	.15	(1.9)	3		1.2	0.94	1.45			
	SMESATM*Intent*SATM	-.26	(3)	10		0.8	0.63	0.95			
	Intercept	-1.38	(23)	608					5170	.43	81.8%
	Ethnicity	-.04	(0.4)	0		1.0	0.732	1.260			
	Gender	.19	(4)	15		1.2	1.068	1.381			
	Intent	2.92	(49)	2,088		18.5	15.691	21.802			
	SATM	.35	(18)	327		1.4	1.356	1.500			
	SATM*Intent	-.12	(3)	11		0.9	0.803	0.972			
	PCTSME	.64	(11)	124		1.9	1.639	2.207			
	SMESATM	-.56	(9)	85		0.6	0.491	0.670			
	PCTSME*Intent	-.40	(3)	12		0.7	0.497	0.900			
	SMESATM*Intent	.37	(3)	9		1.4	1.061	1.971			
	SMESATM*SATM	.08	(4)	15		1.1	1.025	1.134			
	SMESATM*Intent*SATM	-.12	(3)	10		0.9	0.800	0.979			

Table continues

Model	Variable	Parameter estimates				Fit indices			
		$B_k$	$t$	$X^2$	Odds Ratio	99% Wald Conf Limits	LRT	$R^2$ *	ACC
LM <sub>6</sub>	Intercept	<b>-1.40</b>	(47)	1,930			5170	.43	81.8%
	Gender	.19	(4)	15	1.2	1.068	1.381		
	Intent	<b>2.92</b>	(49)	2,105	18.5	15.732	21.835		
	SATM	<b>.35</b>	(18)	350	1.4	1.355	1.494		
	SATM*Intent	<b>-.13</b>	(3)	12	0.9	0.802	0.969		
	PCTSME	<b>.64</b>	(11)	124	1.9	1.639	2.207		
	SMESATM	<b>-.55</b>	(9)	85	0.6	0.492	0.671		
	PCTSME*Intent	<b>-.40</b>	(3)	12	0.7	0.497	0.900		
	SMESATM*Intent	<b>.37</b>	(3)	10	1.4	1.064	1.975		
	SMESATM*SATM	<b>.08</b>	(4)	15	1.1	1.025	1.134		
	SMESATM*Intent*SATM	<b>-.12</b>	(3)	10	0.9	0.799	0.978		

Note. Results are for Black and White participants with complete data on all variables (weighted  $n = 16,616$ ). Coefficients in bold type are significant at  $p < .01$ . \* Baseline -2LogLikelihood (-2LL) = 16373. LRT = reduction from baseline -2LL.  $R^2$  \* = "maximum-rescaled  $R^2$ " (see Appendix C). ACC = % of observed *smegrad* classifications—both yes and no—that are correctly specified by the model given prior probability of *intent* to major in SME = .1945.

Table 1

Percent of Bachelor's Degrees Earned in Engineering and Natural Sciences<sup>a</sup> by Gender and Ethnicity, 1990-1994, as a Function of Respective 22-24<sup>b</sup> Year-Old Populations

Group	1990		1994		1990 to 1994 ifference in Percen
	Percent	( <i>n</i> )	Percent	( <i>n</i> )	
<b>Female</b>					
American Indian	0.39	(175)	0.63	(296)	+0.24
Asian	2.46	(4,457)	2.82	(5,961)	+0.36
Black	0.50	(3,962)	0.69	(5,288)	+0.19
Hispanic	0.40	(2,505)	0.52	(3,371)	+0.12
White	0.96	(38,323)	1.21	(43,938)	+0.25
<b>Male</b>					
American Indian	0.76	(362)	1.03	(497)	+0.27
Asian	4.63	(8,881)	5.10	(10,956)	+0.47
Black	0.51	(3,892)	0.66	(4,930)	+0.15
Hispanic	0.58	(4,363)	0.74	(5,420)	+0.16
White	2.18	(89,381)	2.44	(91,945)	+0.26

Note. Source: NSF, 1999 (Appendix Tables 3-4, 3-5, 3-7). The report included data for each year, 1990 to 1994, and within-group percentage comparisons each year to the next (40) were either equal or increased in all but two cases.

<sup>a</sup> Includes Physical Sciences (astronomy, chemistry, physics, and earth, atmospheric and ocean sciences) and agricultural, biological, computer, and mathematical sciences.

<sup>b</sup> 3/7ths of the 18-24 year-old population estimate by U.S. Bureau of the Census.

Table 2

Sample Selection Effects on Key Variables for *Complete* Sample Relative to C&B/CIRP *Total* and National Reference Samples

Variable	National College-Bound		C&B/CIRP TOTAL		C&B/CIRP COMPLETE	
	Black	White	Black	White	Black	White
N (within ethnicity % of SAT Takers) (% of TOTAL C&B/CIRP)	96,615 ---	<sup>a</sup> 752,257 ---	1,829 (1.9%) (100%)	22,763 (3.0%) (100%)	1,120 (61%)	15,496 (68%)
N with Valid CIRP Survey (% of TOTAL C&B/CIRP)	---	---	1,246 (68%)	16,965 (75%)	1,120 (61%)	15,496 (68%)
% Intending SME Non-Missing Response (% TOTAL)	20% ---	<sup>b</sup> 19% ---	35% 1,181 (65%)	27% 16,238 (71%)	35% 1,120	27% 15,496
Mean SATM (SD) Non-Missing Score (% TOTAL)	386 (99) 96,615	<sup>a</sup> 491 (116) 752,257	533 (93) 1,752 (96%)	631 (88) 21,930 (96%)	531 (90) 1,120	629 (83) 15,496
% SME Graduates Non-Missing Status (% TOTAL)	9% ---	<sup>c</sup> 17% ---	15% 1,766 (97%)	20% 22,412 (98%)	16% 1,120	20% 15,496

Note. C&B = College & Beyond. CIRP = Cooperative Institutional Research Program. <sup>a</sup> 1989 National SAT Takers (Educational Testing

Service, 1989). <sup>b</sup> Within-ethnicity percent of 1989 freshmen intending physical, biological, agricultural or computer sciences, math, statistics or engineering (National Science Board, 2002). <sup>c</sup> Estimated from NSF Report No. 99-338 (NSF, 1999), Appendix Tables 3-1 and 3-22: Number earning BA in Engineering or Natural Sciences in 1995/Number of full-time, first-time, first year 1990 4-year enrollees. This almost certainly over-estimates the figures, however, as the 1995 degrees could be earned by students beginning in any prior year and at different types of schools under different initial enrollment conditions.

Table 3

Variable Description, Numerical Coding and Distribution in Complete Cohort,  $N = 16,616$

(1,120 Blacks, 15,496 Whites)

<u>Coding and Description</u>		<u>Within-Ethnic Group Percentage</u>	
<u>Student-Level Variables</u>		Black	White
<i>smegrad</i>	1 if the student graduated from college with a major in science math or engineering, 0 otherwise.	16%	20%
<i>ethnicity</i>	.5 if self-reported ethnicity is White (93%), -.5 if Black (7%).		
<i>gender</i>	.5 if self-reported gender is Male, -.5 if Female.	64%	54%
<i>intent</i>	.5 if self-reported intended major is in science, math or engineering, -.5 otherwise.	35%	27%
<u>College-Level Variables (<math>c = 24</math>)</u>		<u>Median, Mean, (SD)</u>	
<i>pctsmc</i>	Percentage of 1989 freshman matriculants who graduated with a SME degree from the original institution within six years	21.5, 20.6, (9)	
<i>smesatm</i>	Institutional SATM for students intending a SME major.	638, 652, (43)	

Table 4

Multilevel Models for the Prediction of College Science, Math or Engineering Graduation

Parameter		M <sub>0</sub>	M <sub>1</sub>	M <sub>2</sub>	M <sub>3</sub>	M <sub>4</sub>
<b>Fixed Effect (Level 1)</b>						
Intercept	$\gamma_{00}$	<b>-1.46 (13)</b>	<b>-1.51 (13)</b>	<b>-1.47 (13)</b>	<b>-1.20 (12)</b>	<b>-1.40 (25)</b>
<i>Ethnicity</i>	$\gamma_{10}$		.17 (1.9)	<b>.58 (6)</b>	-.03 (0.3)	
<i>Gender</i>	$\gamma_{20}$		<b>.69 (17)</b>	<b>.44 (9)</b>	<b>.22 (4)</b>	<b>.19 (4)</b>
<i>Intent</i>	$\gamma_{30}$			<b>2.87 (57)</b>	<b>2.79 (55)</b>	<b>2.81 (22)</b>
<i>satm</i>	$\gamma_{40}$				<b>.34 (18)</b>	<b>.35 (18)</b>
( <i>Intent</i> x <i>satm</i> )	$\gamma_{50}$				<b>-.10 (3)</b>	<b>-.12 (3)</b>
<b>Fixed Effect (Level 2)</b>						
<i>pctsm</i> -> Intercept	$\gamma_{01}$					<b>.62 (6)</b>
<i>smesatm</i> -> Intercept	$\gamma_{02}$					<b>-.53 (5)</b>
<i>smesatm</i> -> <i>satm</i>	$\gamma_{42}$					<b>.09 (4)</b>
<i>smesatm</i> -> ( <i>Intent</i> x <i>satm</i> )	$\gamma_{52}$					<b>-.16 (4)</b>
<b>Random Effect</b>						
Intercept Variance	$\tau_0^2$	<b>.30 (3.2)</b>	<b>.26 (3.2)</b>	<b>.23 (3.1)</b>	<b>.16 (3.0)</b>	<b>.04 (2.2)</b>
Slope Variance of <i>Intent</i>	$\tau_3^2$					<b>.26 (2.5)</b>
<b>Goodness-of-Fit</b>						
Deviance (-2 LogLikelihood)	-2LL	15910	15621	11580	11242	11147
$\Delta$ -2LL	LRT	0	289	4330	4668	4763
<b>Intraclass Correlation</b>						
	$\rho_1$	.084	.073	.065	.046	.012
Total Variance of <i>smegrad</i>			3.67	5.30	5.80	5.66
Variance of the linear predictor	$\sigma_F^2$		.12	1.78	2.35	2.33
Proportion Explained Variance	$R^2_{dicho}$		.03	.34	.41	.41
Prop Unexplained at Level 1	UL1		.90	.62	.57	.58
Prop Unexplained at Level 2	UL2		.07	.04	.02	< .01

**Note.** All models were fit with SAS PROC NL MIXED with  $N = 16,616$ , and  $C(\text{colleges})=24$ ; Coefficients shown in bold type are significant at  $p < .05$ . MLE (ln) parameter estimates are listed with approximate  $t = p/se(p)$  in parentheses. *smesatm*, the mean institutional SATM score among SME-intending students, and *satm* are each centered about the grand median among students intending SME (650) and scaled to represent an increment of 50 SATM points. *pctsm* = the percentage of a college's matriculants who graduated in SME, centered around the approximate grand median of 20% and scaled to represent 10 percentage point increments. Following Snijders & Bosker (1999),  $\sigma_F^2$  = observed variance of estimated log-odds (see Appendix A).  $\sigma_R^2$  (Level 1 residual variance) =  $\pi^2/3 = 3.29$ .  $\rho_1 = t_0^2/(t_0^2 + \sigma_R^2)$ ;  $varY = \sigma_F^2 + t_{02} + p^2/3$ ;  $R^2_{dicho} = \sigma_F^2/varY$ ;  $UL1 = \sigma_R^2/varY$ ;  $UL2 = \tau_0^2/varY$ .



## Figure Captions

Figure 1. For each of 11 private colleges, 3 bubbles index percentages of the degrees awarded in the natural sciences earned by students in each third of the within-institution SATM distribution (data from Elliott et al., 1995, Table 10).

Figure 2. Path diagram of hypothesized effects on SME graduation.

Figure 3. Percentage of 1989 matriculants that graduated in SME by mean SATM among SME-intending students for 24 CIRP colleges.

Figure 4. Estimated SME Graduation Probability by Initial Intended Major, Ethnicity and Gender (with 99% CI).

Figure 5. Estimated Probability of Initially Intending SME as a function of ethnicity and gender (with 99% CI).

Figure 6. Boxplots of SAT Math by Initial Intended Major, Ethnicity, and Gender.

Figure 7. Final Model ( $M_4$ ) Estimated Odds Ratios (given initial intended major is SME).

Figure 8. Model  $M_4$ -Estimated Odds of Graduating in SME for a SME-Intending Student with SAT Math = 550 at 24 Colleges.

Figure 9. Empirical Odds of Graduating in SME at 24 colleges for students initially intending SME with SAT Math scores in the 500s.

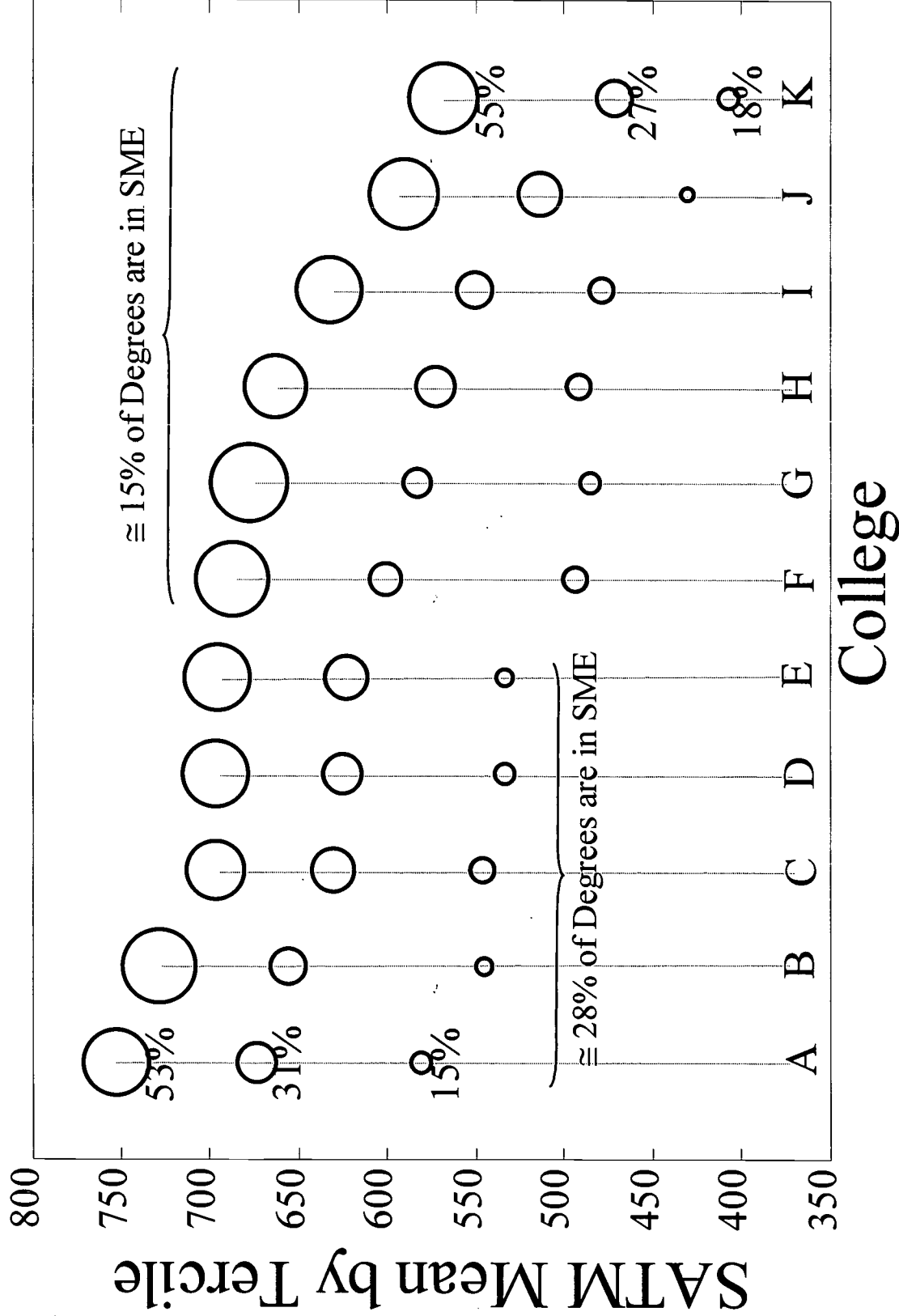


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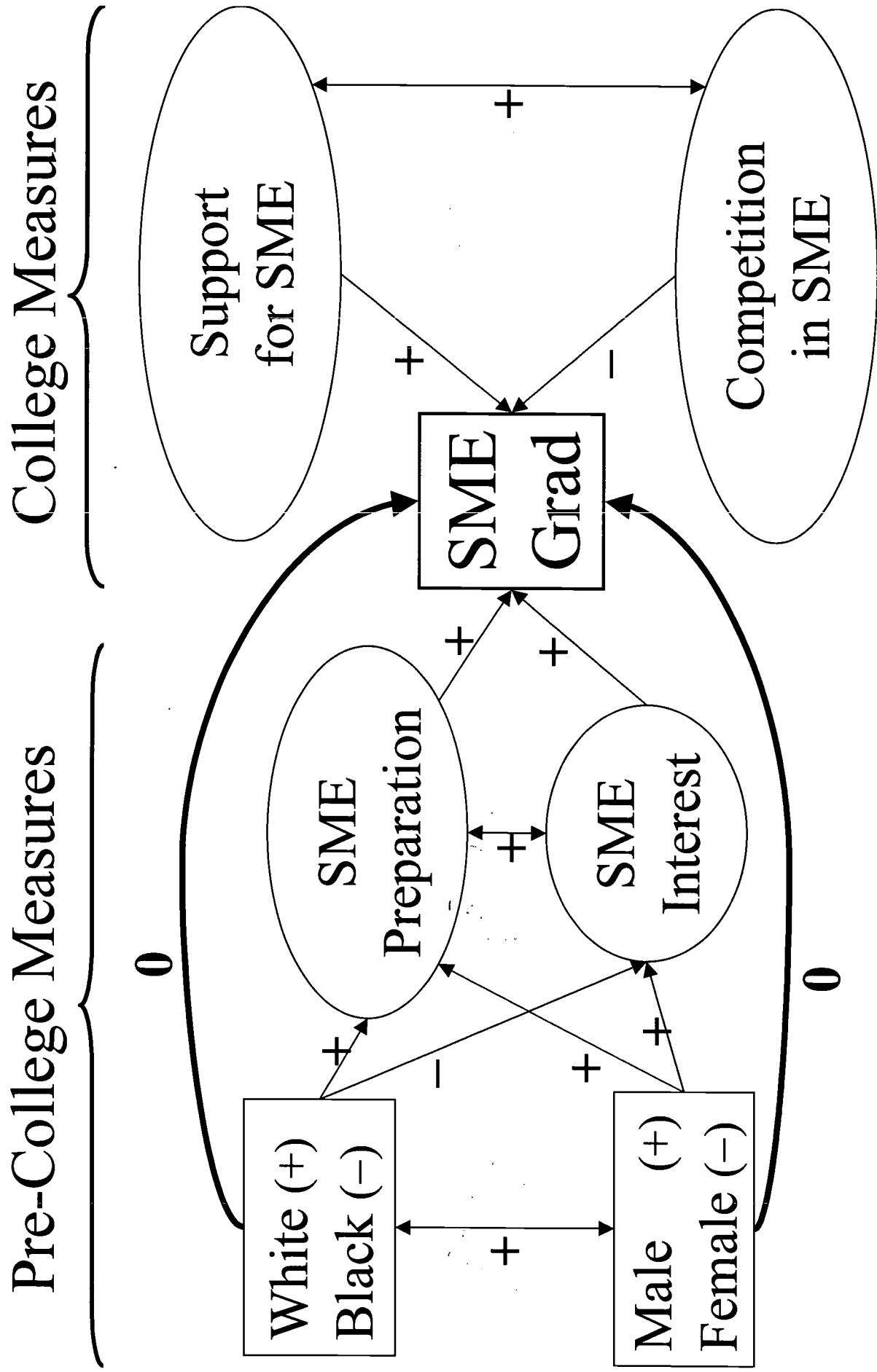


Figure 2. Path diagram of hypothesized effects on SME graduation.

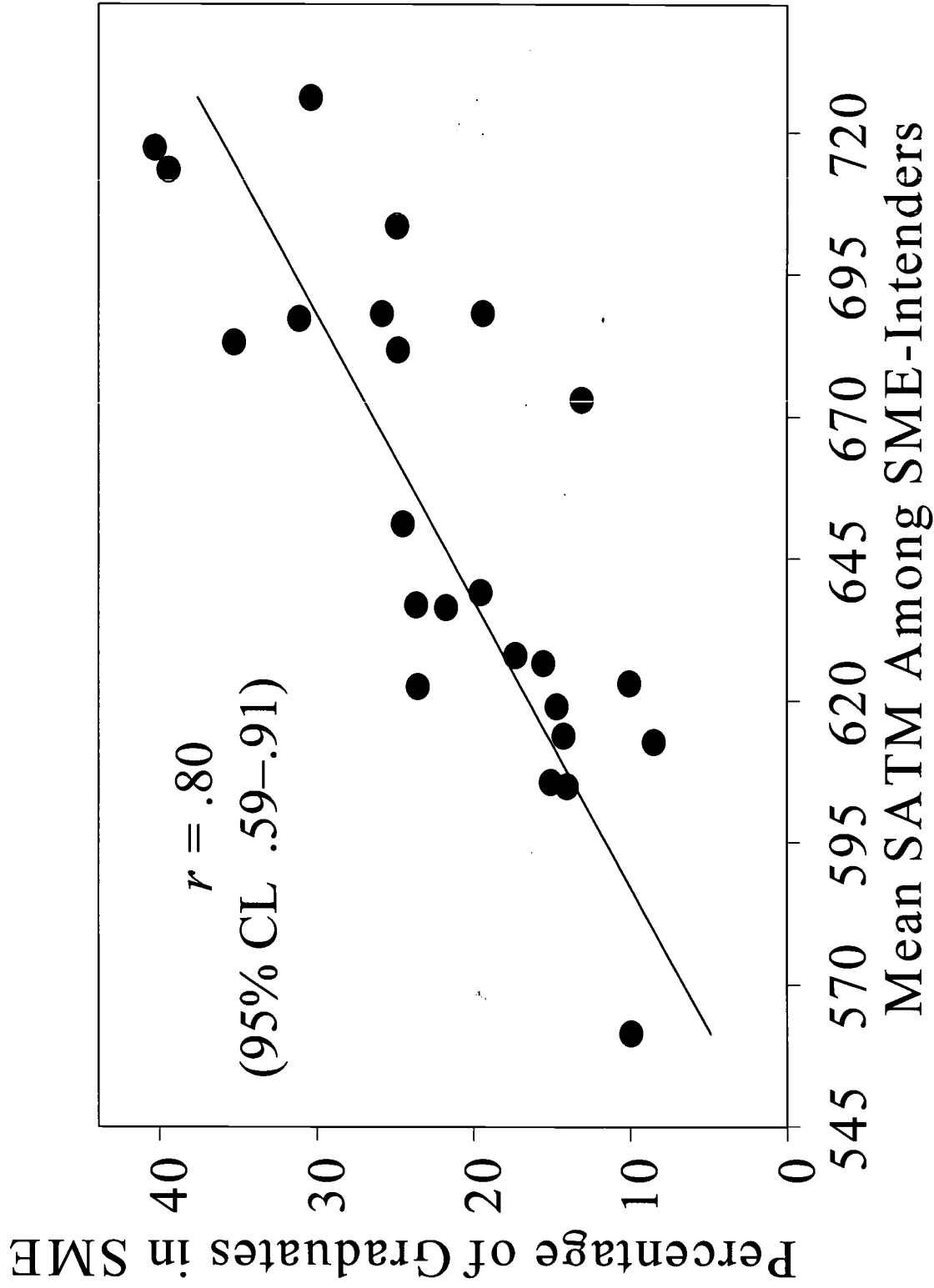


Figure 3. Percentage of 1989 matriculants that graduated in SME by mean SATM among SME-intending students for 24 CIRP colleges.



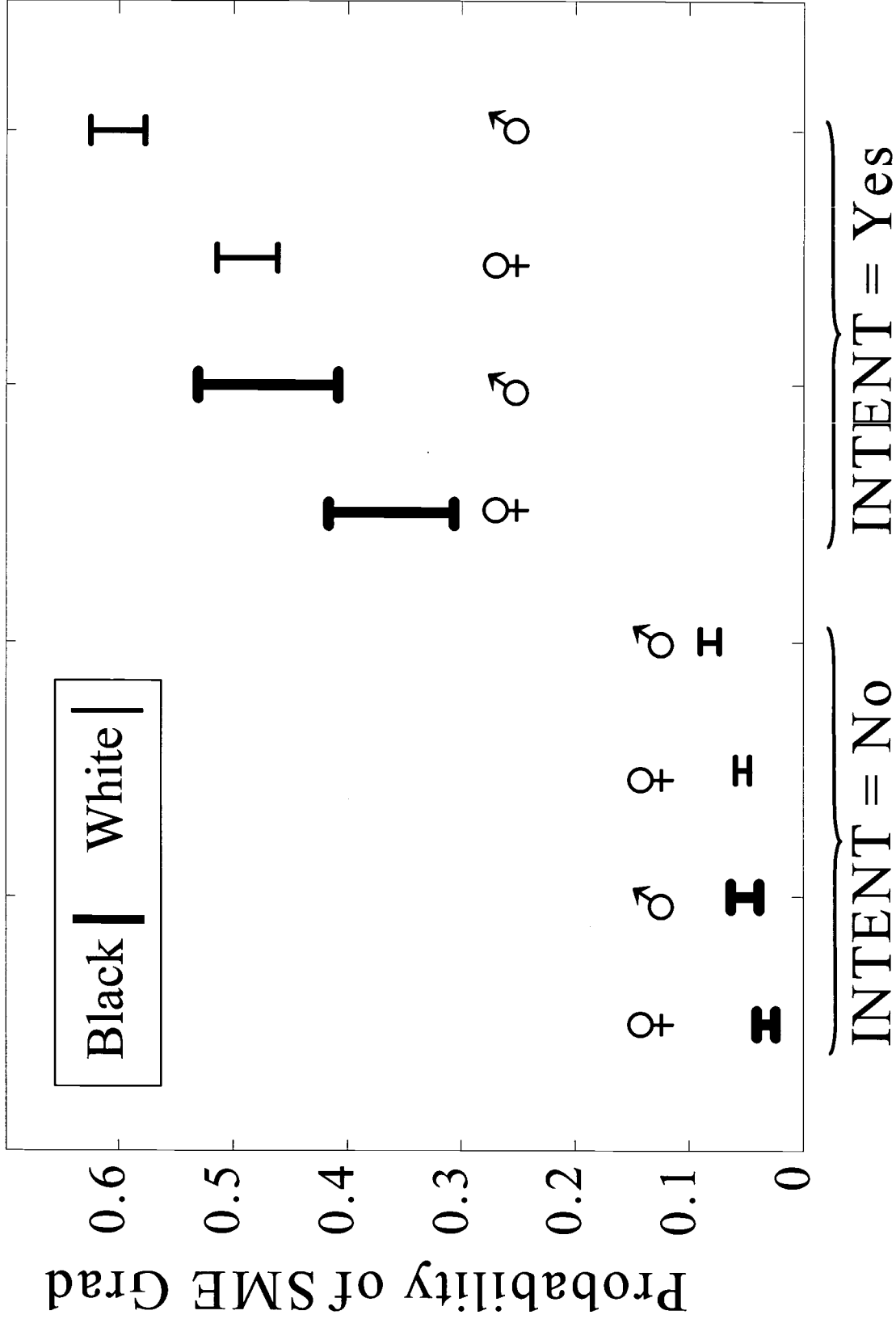


Figure 4. Estimated SME Graduation Probability by Initial Intended Major, Ethnicity and Gender (with 99% CI)

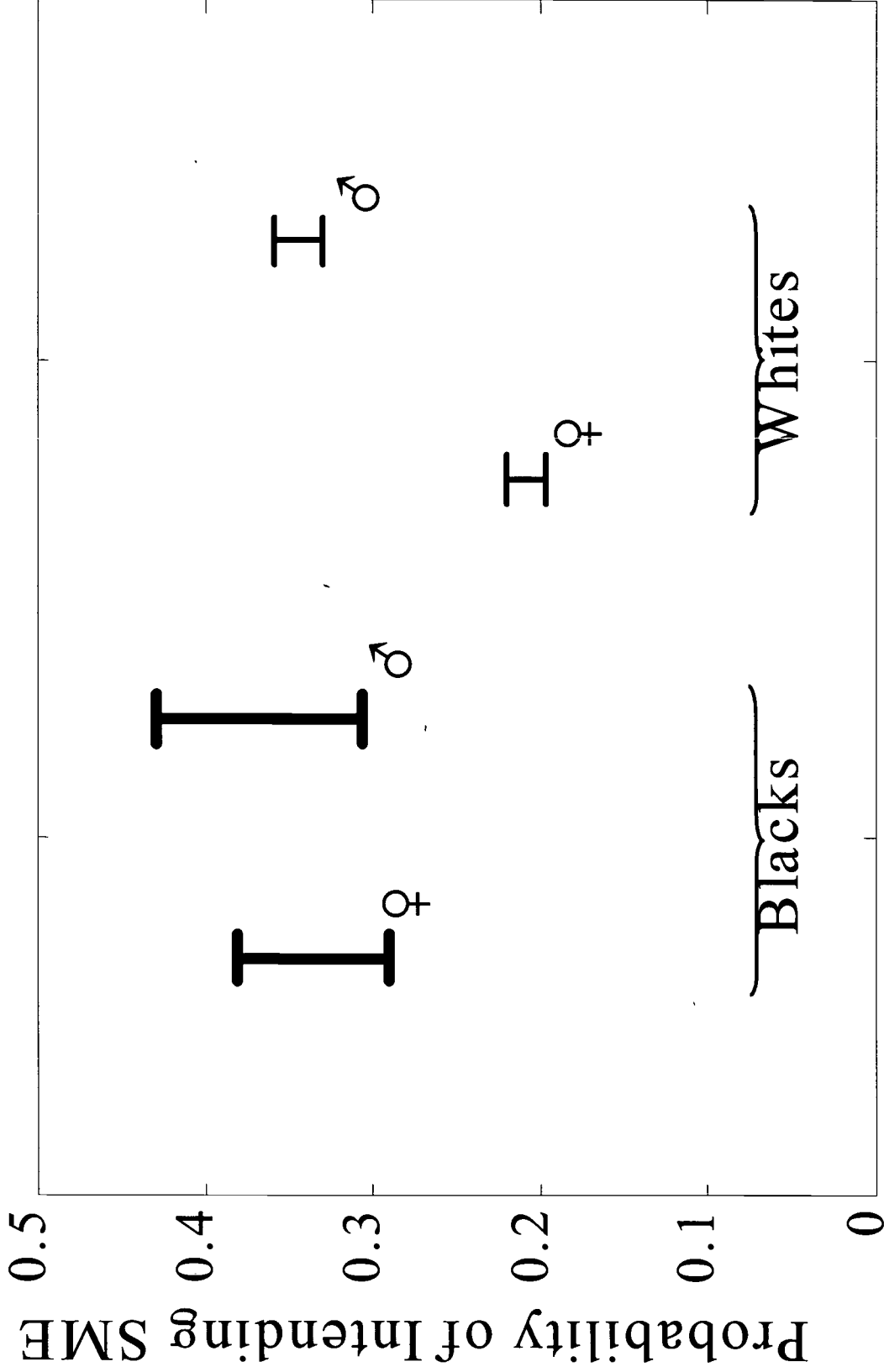


Figure 5. Estimated Probability of Initially Intending SME as a function of ethnicity and gender (with 99% CI).

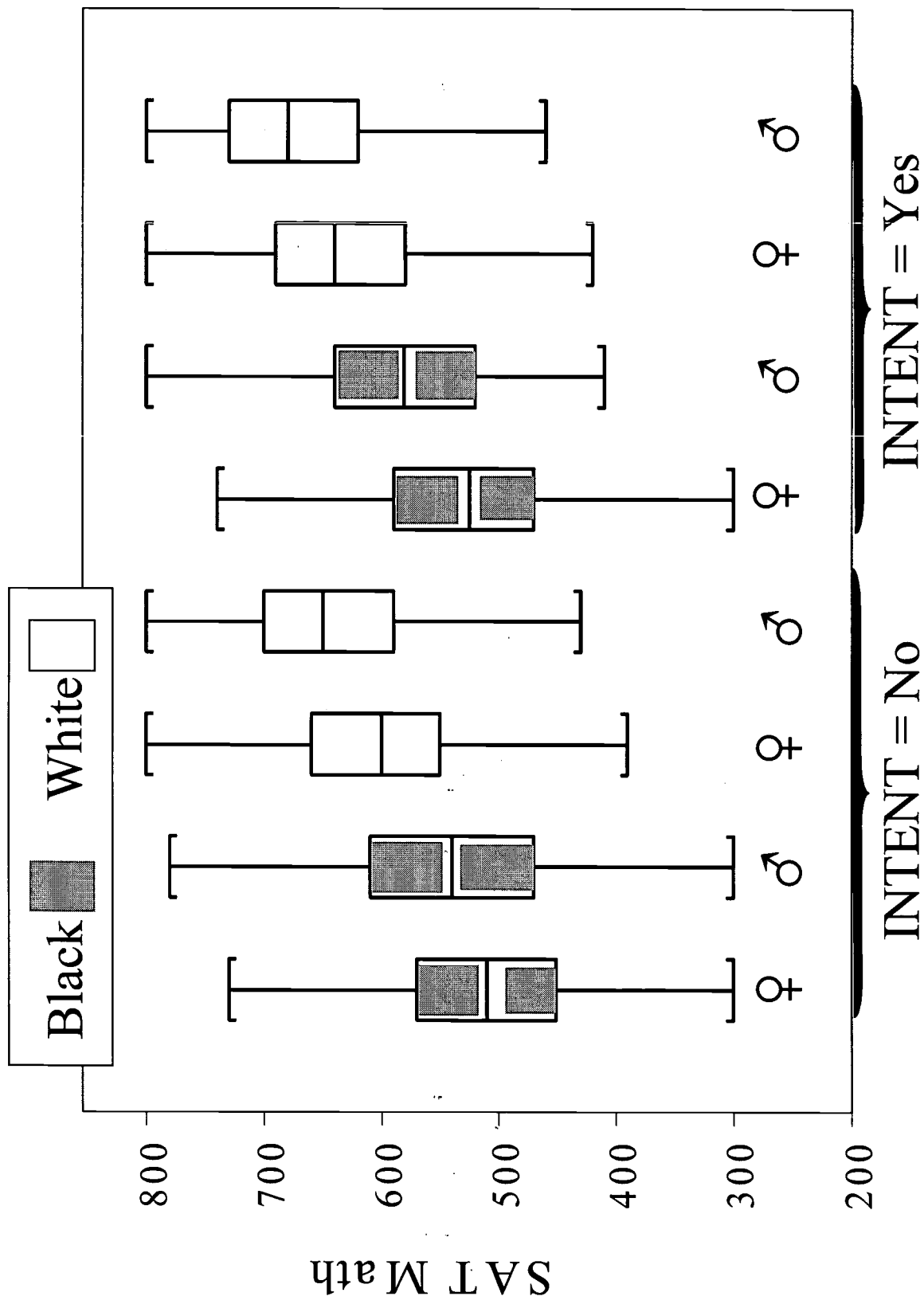


Figure 6. Boxplots of SAT Math by Initial Intended Major, Ethnicity, and Gender.

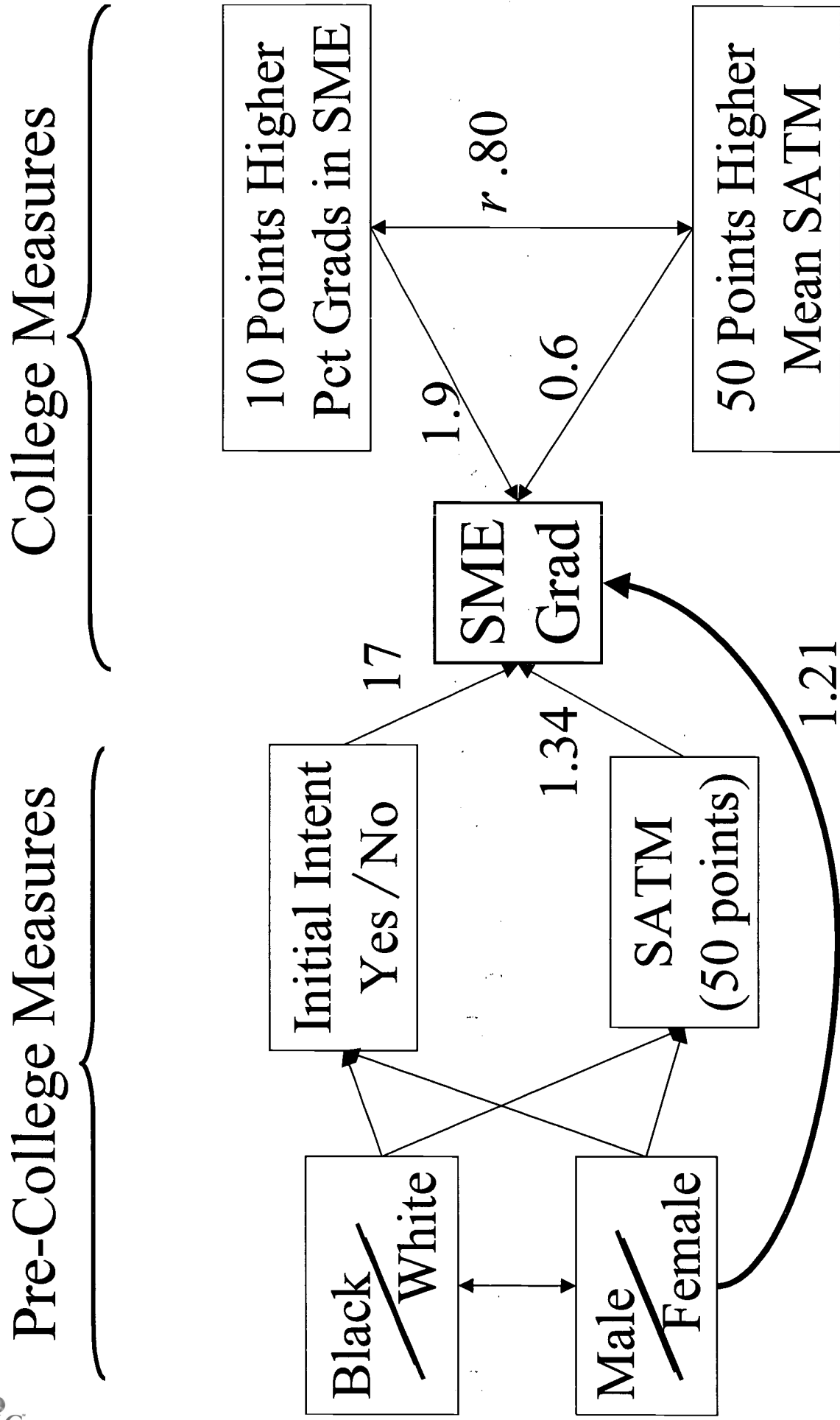


Figure 7. Final Model ( $M_4$ ) Estimated Odds Ratios  
(Given initial intended major is SME)



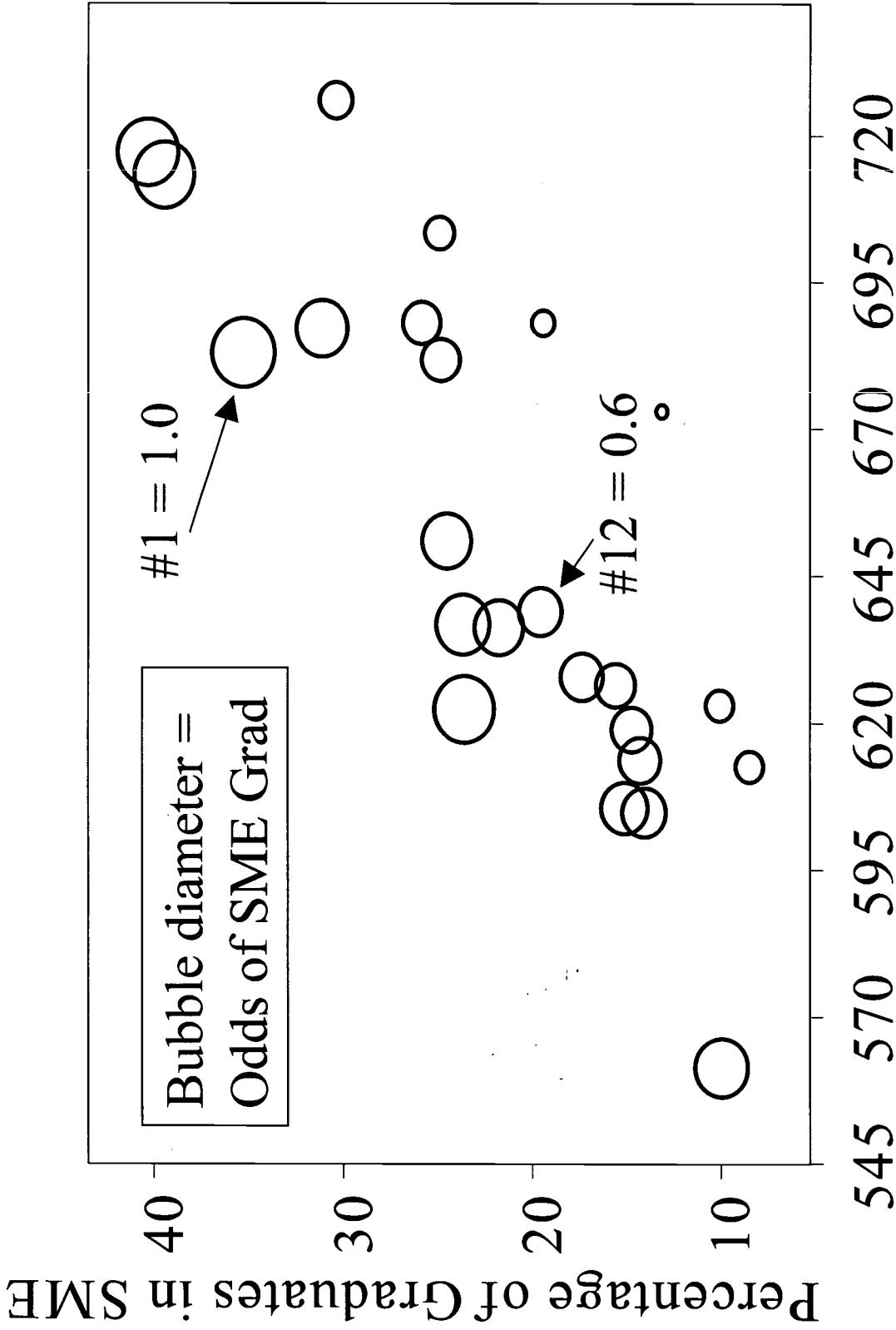
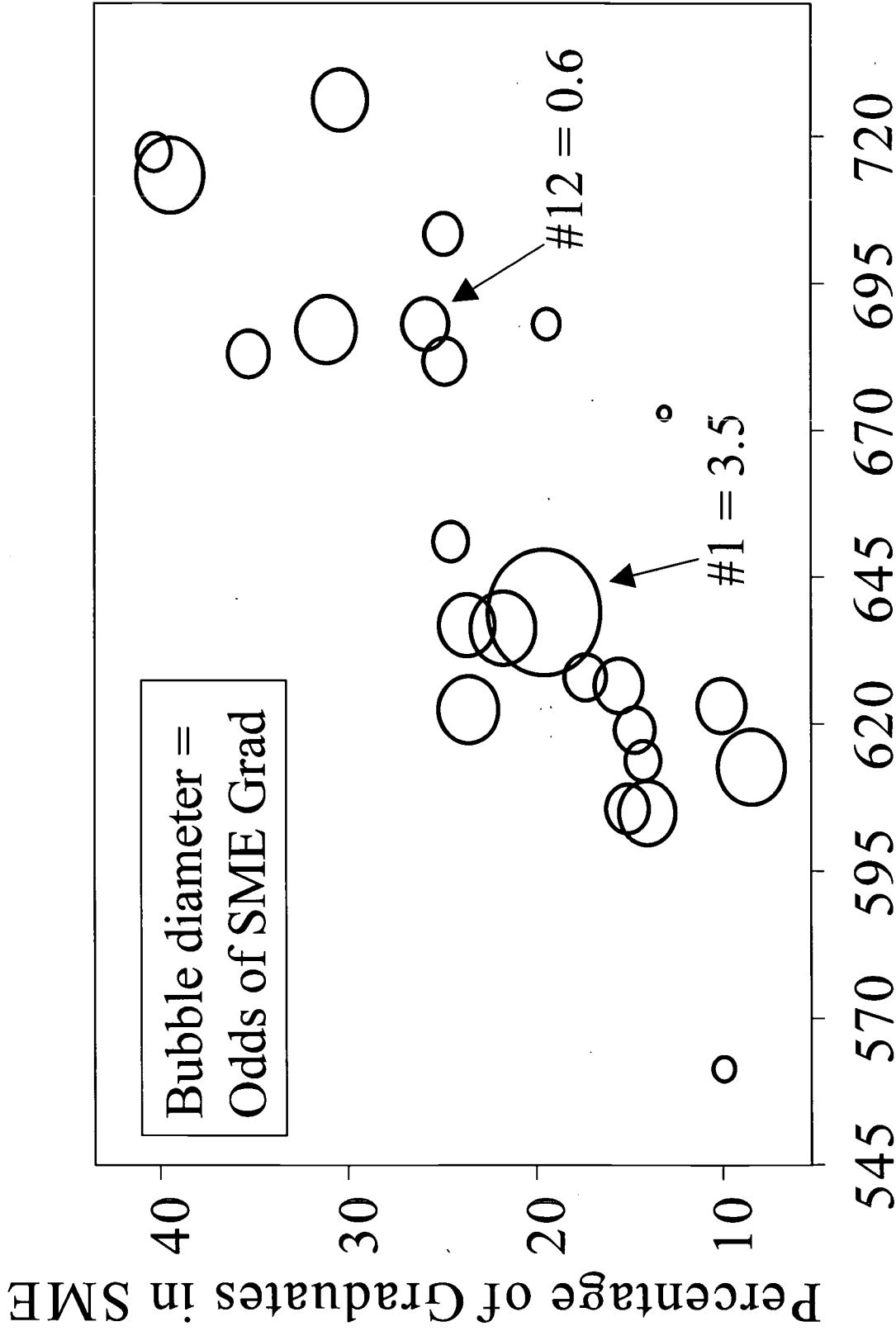


Figure 8. Model  $M_4$ -Estimated Odds of Graduating in SME for a SME-Intending Student with SAT Math = 550 at 24 Colleges.



Mean SATM Among SME-Intenders

Figure 9. Empirical Odds of Graduating in SME at 24 colleges for students initially intending SME with SAT Math scores in the 500s.

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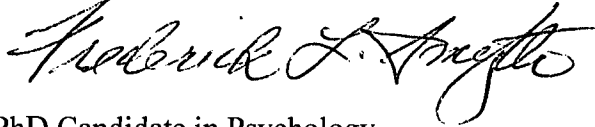
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