Academic Achievement among STEM Aspirants: Why do Black and Latino Students Earn Lower Grades than their White and Asian Counterparts?

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Introduction

One of the primary goals of higher education is to educate cadres of graduates whose talents can be used to improve society. Young scientists are a key part of this future generation, and as technology increasingly becomes part of everyday life, new scientific talent becomes increasingly important. The National Science Foundation (NSF)'s National Science Board notes that science and engineering are primary drivers of both economic growth and national security and that "excellence in discovery and innovation in science and engineering (S&E) derive from an ample and well-educated workforce" (National Science Board, 2003, p. 7). Although the number of students majoring in science and engineering continues to increase as the number of students pursuing postsecondary degrees increases (NSF, 2010), the demand for scientists outpaces the supply (NSF, 2003; National Science and Technology Council, 2000).

Compounding the problem, there is an even more extreme shortage of underrepresented racial minority (URM) students who graduate with degrees in science, technology, engineering and mathematical (STEM) fields (NSF, 2005, 2010). Lower STEM completion rates among Black, Latino, and Native American students results in an undiversified scientific workforce and a relative lack of scientists who are interested in pursuing careers that improve the lives and well-being of minority communities (Sullivan Commission, 2004). Among college freshmen nationally, a promising pool of first-year URM students enter college with a strong academic interest in STEM fields (Hurtado, Cerna & Chang, et al., 2006). However, a large portion of these STEM-interested students fail to complete a degree in STEM, and many fail to complete a degree at all (Higher Education Research Institute [HERI], 2010). Even among those who do complete a degree, URM students lag behind their White and Asian peers in terms of pursual of graduate education. For example, in 2005 only 3.5 percent of Latino/as and 5.2 percent of Blacks aged 25 and older had obtained graduate degrees, compared to 10.8 percent of Whites and 17.4 percent of Asians (KewalRamani et al., 2007).

The reasons for racial disparities in undergraduate and graduate degree attainment rates are complex and doubtlessly include a variety of institutional, structural, and individual factors (cf. Berger & Braxton, 1998; Cabrera, Nora & Castaneda, 1992; Fischer, 2007; Murtaugh, Burns & Schuster, 1999; Nora, Cabrera, Hagedorn & Pascarella, 1996; Reason, 2003; Wrightman, 2003). However, one factor that has consistently been shown to be a key part of the puzzle is college GPA, with lower GPAs associated with higher attrition rates and lower enrollments in graduate school (DeBerard, Spielmans & Julka, 2004; Fischer, 2007; Mullen, Goyette, & Soares, 2003; Murtaugh et al., 1999; Nora et al., 1996; Reason, 2003; Sax, 2001). Research has found that White and Asian students tend to achieve higher GPAs than their Black and Latino/a counterparts, both during the first year of college (which is a critical year, Tinto, 1993) and after all four years (Astin, 1993; Betts & Morell, 1999; Bowen & Bok, 1998; Dennis, Phinney & Chuateco, 2005; Elmers & Pike, 1997; Fischer, 2007; Roth & Bobko, 2000). Research has also shown that the gaps in GPA between Blacks/Latinos and Whites/Asians hold steady even among those students who make it to graduation (Bowen & Bok, 1998; Dennis, Phinney & Chuateco, 2005; Elmers & Pike, 1997; Roth & Bobko, 2000).

This paper seeks to identify the institutional and student-level characteristics that significantly impact the cumulative GPA of graduating seniors, in particular those graduating seniors who entered college with an interest in majoring in STEM. These reasons are important to uncover because not only have lower GPAs been linked to attrition in general (DeBerard, Spielmans & Julka, 2004; Murtaugh et al., 1999; Nora et al., 1996; Reason, 2003; Titus, 2006) and in STEM specifically (Campbell, 1993; Crisp, Nora & Taggart, 2009; Rask, 2010) but they have also been shown to restrict many opportunities after college. Students with lower GPAs enroll in graduate school at lower rates (Mullen, Goyette, & Soares, 2003) and are at a disadvantage in the employment market (Albrecht, Carpenter, & Sivo, 1994; Jones & Jackson, 1990; Loury & Garman, 1995; Pascarella & Terenzini, 2005; Roth & Bobko, 2000; Thomas, 2003). In recent years there have been calls for the increased production of graduate degrees in STEM, particularly among students from diverse backgrounds (Committee on Science, Engineering and Public Policy, 2007; Council of Graduate Schools, 2007). Such a goal cannot be met if URM students continue to achieve at lower levels than their White and Asian peers.

Grade Point Averages: Important, but limited

A student's college grade point average (GPA) represents a key indicator of academic achievement, and GPAs are one of the only quantifiable, agreed-upon measures of academic success in college (Becker, Greer, & Hughes, 1968; Plant et al., 2005). Indeed, grades are one of the few formalized measures of achievement that students receive as indicators of their success and progress in college academic life (Plant, Ericsson, Hill, & Asberg, 2005). However, grades are not perfect measures and can be limited in terms of their assessment of learning, particularly in competitive fields such as STEM. Therefore we take care to note that as a measure of achievement, GPAs have some serious limitations. For example, students can earn high GPAs in college without actually learning (Becker, Greer, & Hughes, 1968), and past research has questioned the validity of grades as accurate assessments of what and how much students have learned in a course (Kohn, 1999; Linn & Gronlund, 2000; Marzano, 2000). College grading can also vary significantly across classrooms, institutions, and disciplines (Barnes, Bull, Campbell, & Perry, 2001; Goldman & Widawski, 1976; Strenta & Elliott, 1987). STEM disciplines in particular have been shown to have more rigorous grading policies than non-STEM disciplines (Angelo & Cross, 1993; Barnes et al., 2001; Rask, 2010).

Further, grades can mean different things in different contexts, depending on whether the grading system is competitive or not. Faculty in STEM disciplines (particularly faculty teaching introductory STEM courses), for example, tend to “curve” more frequently than faculty in other disciplines (Maxwell, 2007), meaning students’ grades in these courses are best interpreted relative to one another rather than absolutely. In addition, grading on a curve can also affect how and how much students learn, as curved grading practices tend to beget a “survival of the fittest” mentality in which students compete with one another for test scores rather than collaborate to learn and internalize course content (Epstein, 2006).

Yet even with the limitations of GPA as a measure of academic success, grades do serve as one of the few signals students receive about their progress in a course or degree program. This point has particular relevance to education in STEM disciplines, given the high proportion of students who enter college intending to major in STEM but do not earn a STEM bachelor’s degree (HERI, 2010). STEM-interested students who initially earn lower grades in college have significantly higher likelihoods of switching to non-STEM majors (Griffith, 2010; Ost, 2010) or leaving college altogether (Campbell, 1993). Rask (2010) suggests that grading practices in STEM fields may deter persistence in those fields, pointing out that if introductory STEM courses adopted grade distributions of introductory English courses, STEM persistence rates could increase by 2-4 percentage points. Such an increase would likely be significant for STEM students, as scholars have linked grades with interest in science, noting that lower grades predict a significantly reduced interest in STEM (Kokkelenberg & Sinha, 2010; Peng, Wright, & Hill, 1995; Seymour & Hewitt, 1997).

Predictors of GPA

While limited, GPA is nevertheless an important college outcome to investigate. As Pascarella and Terenzini (2005) note, “grade-point averages are the lingua franca of the academic instructional world, the keys to students’ standing and continued enrollment, to admission to majors with enrollment caps, to program and degree completion, to admission to graduate and professional schools, and to employment opportunities” (p. 396). This study investigates predictors of cumulative college GPAs among students who enter college intending to major in STEM. In particular, we seek to determine whether and why URM STEM students obtain lower GPAs than their White and Asian counterparts. Three research questions guide the study:

1. Among students who entered college with an interest in majoring in a STEM field, do URM students graduate with lower cumulative college GPAs than White students, after controlling for relevant background characteristics?
2. If URMs have significantly lower GPAs, can these differences be explained by student-level characteristics?
3. If not, can institutional characteristics account for the differences?

Predictors of GPA

A large number of factors can influence a students’ college GPA, and these occur both between and within institutions.

Student-Level factors influencing GPA

Much of the difference in students’ college GPAs can be explained by student-level characteristics and experiences. A number of factors have been shown to predict college grades, including race/ethnicity, gender, and socioeconomic status (Robbins, Allen, Casillas, & Peterson, 2006). All other things being equal, Black and Latino/a students (Bowen & Bok, 1998), male students, and students from lower socioeconomic backgrounds tend to earn lower college GPAs (Robbins, Allen, Casillas, & Peterson, 2006). Many researchers point to a student's high school academic achievement to explain the range in student performance in college. However although high school grades and scores achieved on standardized tests are consistently strong predictors of college GPA (Cole, 2008), they do not explain all of the variance in college grades (Burton & Ramist, 2001; Elmers & Pike, 1999; Pike & Saupe, 2002) nor do they have the same predictive validity for different racial/ethnic groups (Bowen & Bok, 1998; Burton & Ramist, 2001; Cohn, Cohn, Balch, & Bradley, 2004; Fischer, 2007). In particular, Black and Latino students have lower overall GPAs than what would be expected based on their high school grades and college-admission test scores (Cole & Barber, 2003). The fact that differences in college GPA are only partially explained by background characteristics and previous academic achievement suggests that it is worth considering other student-level factors, including college experiences, that may influence the grades students earn (Fischer, 2007; Hurtado, Tran, Eagan, Newman, Chang, & Velasco, in press).

The literature on college achievement suggests a long list of factors that generally influence the GPA of college students. Students who have higher perceptions of academic ability (Cole, 2008), self-efficacy (Zajacova, Lynch, Espenshade, & 2005), and academic optimism (Solberg Nes, Evans, & Segerstrom, 2009) are more likely to have higher college GPAs. Further, how students approach schoolwork is as important as how they perceive themselves. Specifically, students tend to perform better in their college classes when they have an organized approach to planning, study in a quiet solitary environment (Plant, Ericsson, Hill, & Asberg, 2005), and have strong study habits and skills (Credé & Kuncel, 2008).

The social realm of college life is also important to college grades. Students who engage in too little or too much social activity tend to have lower levels of academic performance in college (Robbins, Allen, Casillas, & Peterson, 2006). Working long hours or partying for large amounts of time predicts significantly lower college GPAs (Plant, Ericsson, Hill, & Asberg, 2005; Rochford, Connolly, Drennan & 2009). In addition, the quality of relationships that students develop on campus—with one another and with faculty—also impacts how well students perform in college. Students who feel connected to and supported by their peers (Dennis, Phinney, & Chuateco, 2005) and professors (Cole, 2008) tend to have higher grades than those who feel less connected or isolated. Indeed forging connections to faculty members and developing friendships with other students further integrates students into the campus environment and has been shown to assist in college adjustment, which itself is associated with better academic performance (Anaya & Cole, 2001; Fischer, 2007; Jamelske, 2008; Miller, Pyke, Wintrow, Schrader, & Callahan, 2009).

Factors influencing STEM students specifically

The college performance literature on STEM students reveals that high academic achievers have more domain-specific knowledge, more adaptive motivational beliefs, and better self-regulation than their counterparts who earn lower grades (van der Stoep, Pintrich, & Fagerlin 1996). High achievers also hold particular beliefs and attitudes toward their courses instructors and program. For example, a study on computer science students demonstrated that students earning high grades were more likely to report feeling that the atmosphere in their department was friendly and that their courses encouraged teamwork (Beyer, 2008). By contrast, students performed worse when they felt overwhelmed by the work, found the classes difficult, and felt tense about assignments. Poor achievers also had the tendency to believe that their instructor had unrealistic expectations of students and was insensitive to their needs (Beyer, 2008).

Various campus-facilitated experiences appear to aid in the academic performance of students majoring in STEM fields. For example, participants of STEM-focused academic support programs (Navarra-Madsen, Bales, & Hynds, 2010) and supplemental instruction workshops (Barlow & Villarejo, 2004; Rath, Peterfreund, Xenos, Bayliss, & Carnal, 2007) were more likely to earn higher cumulative grades than non-participants, even when controlling for previous ability (Drane, Smith, Light, Pinto, & Swarat, 2005; Matsui, Liu, & Kane, 2003). In one particular study, URM students participating in STEM supplemental instruction workshops had significantly lower average high school GPAs than their White and Asian counterparts; however, the URM students experienced larger gains from the workshops in terms of the grade received in their introductory STEM class than did White and Asian participants (Rath et al., 2007). These findings suggest that enrichment programs that specifically target STEM students have the potential to partly compensate for poor academic preparation in high school (Barlow & Villarejo, 2004).

Students who conduct research with a faculty member also tend to earn higher grades than students who are not involved in research (Barlow & Villarejo, 2004; Sabatini, 1997). Barlow and Villarejo (2004) found that students who participated in undergraduate research were more likely to graduate in their STEM major with a 3.0 or better than students who did not participate. Although conducting undergraduate research positively predicts GPAs for all students, Black students particularly appear to benefit academically from undergraduate research experiences (Kim & Sax, 2009). Other benefits associated with undergraduate research experiences include a better comprehension of STEM fields (Sabatini, 1997), an awareness of what a career in scientific research would involve (Kinkead, 2003; Lopatto, 2004), clarified graduate school or career plans (Hurtado, Cabrera, Lin, Arellano, & Espinosa, 2009; Kardash, 2000; Sabatini, 1997), and a greater belief in one's ability to perform well in one's science classes (Gándara & Maxwell- Hurtado, et al., 2009; Jolly, 1999; Mabrouk & Peters, 2000).

Factors Influencing URM Students

The literature on underrepresented college students highlights the importance of positive student-faculty interactions on performance. Indeed, receiving guidance, support, and encouragement from faculty mentors is associated with higher grades for black, Latino, and Native American students (Cole, 2008, 2010; Fischer, 2007; Mayo, Murguia, & Padilla, 1995), and is especially helpful for students in the sciences (Anaya & Cole, 2001; Cole & Espinoza, 2008; Torres & Solberg, 2001). Conversely, receiving critical corrective feedback from faculty regarding academic work predicts lower college GPAs among Black, Latino, and Asian students (Cole, 2008, 2010).

It would be a mistake to assume that a given intervention or experience has the same general impact for all students. The fact that the student body is more diverse than ever before in terms of age, socioeconomic status, and racial/ethnic background suggests that college experiences may impact students differently (Pascarella, 2006). That is, the impact of an intervention may vary in size and direction depending on the characteristics and traits of students (Pascarella, 2006). Indeed, several studies on college GPA demonstrate that various college experiences and environments differentially influence academic performance based on student racial/ethnic background (Cole, 2008, 2010; Fischer, 2007; Kim, 2006; Kim & Sax, 2009; Lundberg and Schreiner 2004). Kim and Sax (2009), for example, curiously found that course-related faculty interactions predict higher college GPAs for all groups except African-Americans students. Furthermore, although tutoring another college student predicts higher college GPAs for both Black and Latino students (Cole, 2008), studying with other students has a negative association with college GPA for Latino and White students (Fischer, 2007).

The association between social ties and college GPA also varies by race. For White and Black students, having more ties off-campus is negatively linked to college grades but does not seem to detrimentally influence the grades of Asian and Latino students (Fischer, 2007). For non-White groups, having more extensive formal ties and being more involved in school clubs and other formal social activities positively relates to college grades (Fischer, 2007). Other factors that differentially predict GPA by racial/ethnic group include participating in class discussions, spending more time on schoolwork, and interacting with college peers and faculty members (Cole, 2010; Cole & Espinoza, 2008).

Institutional Differences in Grading

In addition to significant differences in grades and grading practices across disciplines, scholars have identified important variations in academic achievement across institutions (Culpepper and Davenport, 2009). Unfortunately, the vast majority of studies examining college GPAs use single-institution samples or have institutional samples that are too small to examine differences across institutions (Culpepper & Davenport, 2009; Young, 2001). Even with this limitation, however, a few studies have identified significant variation in college grades between higher education institutions. Kuh and Hu (1999), for example, identified significant differences in grades across Carnegie classifications with students in doctoral universities earning significantly higher grades than students in all other institutional types throughout the 1980s. However, Kuh and Hu noted that these significant differences disappeared by the mid-1990s. In fact, by the mid-1990s, students at research universities surpassed their peers at doctoral institutions in terms of college grades. Within specific racial groups, however, these differences in GPA by institutional type may not hold, as Cole (2010) found that Asian students attending doctoral and comprehensive institutions earned significantly lower grades than their Asian peers at liberal arts colleges; no differences in academic achievement levels across institutional types were found for Black or Latino students.

Examining the connection between institutional selectivity and Black students' college GPA, Cole (2011) found that selectivity had no significant relationship with Black students' college academic performance. Other studies connecting selectivity to student outcomes have reported mixed results. Students attending more selective institutions have significantly higher likelihoods of persisting in college (Titus, 2006); however, in regard to academic major persistence, selectivity negatively predicts remaining in STEM majors. This finding applies to all students and is particularly important for URM students (Chang, Cerna, Han, Saenz, 2008).

In addition to type and selectivity, scholars have identified institutional enrollment as a significant predictor of college GPA. Robbins et al. (2006) found that students at larger institutions tended to earn significantly lower first-year cumulative GPAs than their peers attending smaller institutions. By contrast, Cole (2010) found that institutional size significantly and positively predicted Asian and Latino students' cumulative GPA but had no significant relationship with GPAs for Black students.

Although not directly tied to students' level of academic achievement, other studies have connected institutional differences to other student outcomes. For example, Allen (1992) and Nelson Laird et al. (2007) concluded that historically Black colleges and universities (HBCUs) provide Black students with greater levels of support. Black students at HBCUs, for example, report significantly more frequent and supportive interaction with faculty than their Black peers at predominantly White institutions (Hurtado, Eagan, Tran, Newman, Chang, Velasco, in press). Differences in outcomes for Black students at PWIs and HBCUs have been attributed to racial isolation and feelings of alienation among Black students at PWIs (Allen, 1992; Pascarella & Terenzini, 2005).

Limitations of the literature

Although a great deal of research explores the relationship between college GPA and different types of college experiences, the current literature is limited in that it largely fails to use a racially/ethnically diverse sample of students. In fact many studies either do not report the ethnic/racial makeup of the students sampled (Credé & Kuncel, 2008; Gibbison, et al., 2010; Plant et al., 2005; Zimmerman, 2003) or rely on samples that are composed of 90% or more White students (Jamelske, 2009; Solberg Nes et al., 2009). When minority students indeed represent a larger portion of the sample examined, results are either not disaggregated by race/ethnicity (Robbins et al., 2006; Zajacova, Lynch, Espenshade, & 2005) or are presented in a White/Black (Pino & Smith, 2004) or majority/minority (Rath et al., 2007) dichotomy. Since these studies do not disaggregate findings by particular race/ethnicity, it is difficult if not impossible to determine whether specific experiences uniquely impact specific racial/ethnic groups.

Another limitation of the current literature on academic achievement is that most studies do not use data longitudinally (Credé & Kuncel, 2008; Gibbison, et al., 2010; Plant et al., 2005; Zimmerman, 2003). This design effectively precludes the researcher from determining whether the impact of some intervention or experience is real and persists or if the impact fades away with time (Light, Singer & Willett, 1990). Furthermore, a large number of current studies also do not collect data from multiple institutions (Gibbison et al., 2010; Pino & Smith, 2004;

Rochford et al., 2009;) or from different types of institutions (Fisher, 2007). This makes it difficult to generalize the findings to other populations of students. The current study seeks to address some of these limitations ,investigating predictors of GPA employing longitudinal data drawn from a large, racially/ethnically diverse group of students attending hundreds of institutions across the country.

Methods

Data and Sample

Data for this study come from the Cooperative Institutional Research Program (CIRP)'s 2004 Freshman Survey (TFS) and 2007-08 College Senior Survey (CSS). The CIRP is a program of data collection and research housed at the Higher Education Research Institute (HERI) at the University of California, Los Angeles. The TFS and CSS are administered annually by CIRP to college students across the U.S., and each survey collects a wide variety of information about students (see Liu, Ruiz, DeAngelo & Pryor, 2009 and Sax, Hurtado, Lindholm, Astin, Korn, & Mahoney, 2004 for more information about these surveys). The 2004 TFS was administered to first-year students entering college in the summer/fall of 2004, either during freshman orientation or during the first few weeks of the fall term. The 2008 CSS followed up with this same group of students in the spring of or summer after their fourth year in college. The 2008 CSS data were linked to the 2004 TFS data to form a longitudinal dataset that tracked students over their first four years of college. Based on this matching, the estimated longitudinal response rate for the TFS-CSS was approximately 23%. To the longitudinal database, we added institution-level data from academic year 2006-2007, drawn from the Integrated Postsecondary Education Data System (IPEDS).

The sample for this study was drawn intentionally with the goal of obtaining a large and diverse sample of students from three groups: (1) URM groups who were interested in STEM, (2) a set of their White and Asian American STEM counterparts, and (3) a set of URM students not interested in STEM. Grants from the National Institutes of Health (NIH) and National Science Foundation (NSF) provided funds to sample these targeted groups. Specifically, a grant from NIH allowed for the specific recruitment of students at minority-serving institutions that have strong reputations of graduating undergraduates in the biomedical and behavioral sciences, as well as students at institutions that have NIH-funded undergraduate research programs. Further funding from NSF allowed us to expand our sample to include students at institutions that have strong reputations for producing bachelor's degrees in STEM. For the specific sample in this study, analyses were limited to the 4,122 students attending 224 institutions who upon matriculation indicated an interest in majoring in a STEM field.

Variables

The dependent variable used in this study was a self-reported measure of students' cumulative GPA as of the time that the CSS was given. Students could classify their GPA in one of 8 categories, from 1 = D to 8 = A or A+.

The selection of the independent variables in the model was guided by the literature on predictors of GPA as well as conceptual models described by Pascarella (1985), Berger and Milem (2000), and Weidman (1999), all of whom emphasize the importance of taking into account student background characteristics, organizational characteristics, academic and social interactions with the organization, peer groups, and student effort when examining student outcomes. The variables chosen for the current analysis are shown in Appendix A. They include student demographics and background characteristics; high school achievement; push/pull factors such as time spent working, financial concerns, and family support; different types of faculty-student interactions; formal and informal academic activities, such as studying with other students and joining a major-related club; social integration; racial climate and cross-racial interactions; and students' sense of belonging on campus. We also controlled for students' majors, grouping majors into five groups: non-STEM, Biological sciences, Engineering, Health and Health Technology, and Physical sciences and Math.

In addition to the student-level we also modeled institution-level variables. These included institutional type and control (4-year/university, public/private), institutional selectivity (measured by the average SAT score of entering freshmen), percent of students majoring in STEM fields, structural diversity (percent of student body that is Black, Native American or Latino/a), whether an institution is a historically Black college or university (HBCU), and institutional size (as measured by undergraduate FTE). Appendix A describes all variables in the analysis.

Analysis

Missing data. In order to maximize the sample available for analysis, missing data were replaced, wherever appropriate, in a several-step process. First, we removed from our samle all students who had missing data on the dependent variable. Next, we removed all students who were missing information on key demographic characteristics, such as gender and race, as well as those missing high school GPA. In total, 54 students were missing information in one or more of these areas (1.3%). For the remaining variables of interest, we analyzed the extent to which missing data occurred. Overall, there was very little missing data; only two variables had more than 6% of cases missing. The SAT variable had the highest proportion of missing data, at 10.7%, followed by parental income, at 8.1%.

Given the relatively few instances of missing data across the variables used in the analysis, we elected to fill in missing data using the expectation maximization (EM) algorithm in SPSS 17.0. The EM algorithm employs maximum likelihood estimation techniques to impute values for cases with missing data, and because it uses most of the information available in the dataset to produce the imputed values, it is a more robust method of dealing with missing data than listwise deletion or mean replacement (Allison, 2002; Dempster, Laird, & Rubin, 1997; McLachlan & Krishnan, 1997). Distributions of variables were compared before and after missing values were imputed, and were found to be virtually identical.

Weighting. Because of the relatively low longitudinal response rate for the TFS-CSS (23%), weights have been calculated to adjust for any nonresponse bias that might be present. The aim of this weighting, performed on the entire CSS sample, was to adjust the longitudinal sample of respondents to look like the original population of TFS participants. To complete the first step of the weighting process, we used data from the National Student Clearinghouse and institutional registrars to remove non-completers from the 2004 TFS data to make the initial sample consist of only those students who persisted for at least four years. In the second step, we used the persisting cohort of students and logistic regression to predict the probability of responding to the CSS. Predictor variables came from the 2004 TFS and included indicators of race, gender, high school achievement, and reasons for attending college. (A full list of variables in the model is available upon request.) We then used the coefficients from the significant predictors in the model to calculate out the probability that a student would respond to the CSS, and these response probabilities were inverted to develop response weights.[1]

After calculating response weights, we compared the weighted and un-weighted samples from 2004 to determine whether our weights inappropriately skewed any of the 2004 Freshman

[1] The general formula for developing a non-response weight is: weight = 1/(probability of response).

Survey variables. After confirming that the weight had not adversely affected the distributions of variables from the 2004 Freshman Survey, we created a final weight that was normalized to account for sample size. This was calculated by dividing each student's response weight by the average population response rate, and was done in order to avoid inflating any statistics calculated in regressions or other analyses on the weighted sample. All analyses performed for this study were done using data weighted by the final, normalized weight.

Validity of self-reported GPA. Because the dependent variable (GPA) in this study is self-reported, it is possible that it does not accurately reflect students' actual achievement. To assess whether this was a concern with our data, a validity study on self-reported GPA was performed. This was accomplished using a set of data collected from institutional registrars, which was available for approximately half the sample (n = 2,568). The registrar data, which was merged into the longitudinal TFS-CSS file, contained actual cumulative GPA at the end of the spring of 2008, coded on a traditional 4-point scale. To compare it to the CSS self-reported GPA, the CSS variable was re-coded from its original 8-point format to the equivalent 4-point format by converting the letter grades (A, A-, B+, B, etc.) into their numeric equivalent (4, 3.7, 3.3, 3, etc.), and the registrar data was re-coded to match, using rounding rules (3.49 became 3.3, for example, and 3.51 became 3.7). Correlations between the self-reported and actual GPA (original scale and re-coded scale), as well as cross-tabs between these variables (re-coded scales), were examined. Correlations between the registrar and self-reported GPAs were 0.77, both for the two variables as originally coded, and 0.78 for the two recoded variables. Based on the cross-tabulations between the two recoded GPA variables, we discovered that 90% of students accurately reported their GPA within 0.3 points, with approximately equal numbers students self-reporting a GPA 0.6 points or more lower than their actual GPA (4%) and 0.6

points or more higher than their actual GPA (6%). Over-reporting was more prevalent among students with GPAs under 2.7 (28% of these students reported their GPA as being 0.6 points or more higher than reported by the registrar), but these students made up less than 10% of the sample. On the whole, students seemed fairly accurate in their self-reported GPA. Therefore, in order to employ the largest sample size we elected to use self-reported GPA over the registrar-reported GPA in our analyses.

Multi-level analysis. The clustered, multi-level nature of our data necessitates the use of hierarchical linear modeling (HLM). HLM is an ideal statistical technique for our data, as it separates individual and institutional effects so that the both individual characteristics and institutional contexts that affect academic achievement can be examined. Performing single-level analyses with multi-level data can underestimate the standard errors of model parameters, which inflates Type-I statistical error (de Leeuw & Meijer, 2008; Raudenbush & Bryk, 2002). To ensure the use of HLM was justified, a fully unconditional model (i.e., a model with no predictors) was run to assess whether the cumulative college GPAs of STEM aspirants significantly varied across the institutions in our sample. Although differences within institutions (i.e., across students) accounted for the vast majority of variance in cumulative college GPA, the level-2 variance component in the null model was significant, with approximately 8.2% of the variation in students' GPAs attributable to differences between institutions.

To answer the three research questions guiding the study, our analyses were done in several stages. Specifically, we first examined the impact of race and gender without any other predictors in the model. We next added high school achievement to the model to see if any observed differences between groups could be accounted for by differences in academic preparation. Third, we added other relevant pre-college background characteristics, and fourth, we added students' final major, followed by college experiences. Finally, institution-level variables were added in the last step.

Additional modeling considerations. When using hierarchical modeling, analysts must make choices regarding the centering effects of variables. We were interested in the average effect of each predictor on students' GPAs, so we chose to grand-mean center all continuous variables. Grand-mean centering subtracts the mean of the variable for the entire sample from each individual observation, and allows the model intercept to be more easily interpreted (Raudenbusch & Bryk, 2002). Dichotomous variables were left un-centered because a 0 value on these variables is meaningful.

Limitations

Before presenting and interpreting the results of our analyses, it is important to take note of some limitations of this study. First and foremost, our sample includes only students who were still enrolled or were graduating at the original institution they enrolled in, after four years of college. In other words, students who withdrew, stopped out, or transferred are not included in the sample, and thus our results apply only to those students who were successful in persisting for four years. Likely, the composition of our sample restricts the cumulative college GPAs that were observed because students usually must maintain a minimum GPA to stay enrolled in college.

A related limitation of our study is that the CSS had a relatively low longitudinal response rate (23%), and thus the extent to which our results are generalizable to a larger group of students may be limited. Although we attempted to correct for the nonresponse bias that may have been introduced by the low response rate, our correction was necessarily limited to the information we had available, and we may not have taken all important factors into consideration. Finally, this study employs GPA as a proxy for academic achievement. As discussed in the first portion of this paper, GPA cannot possibly represent the sum total of the learning a student experiences in college, and results must be interpreted with this in mind.

Results

Descriptive statistics for all variables used in the analysis are shown in Table 1. On average, students had cumulative college GPAs of 5.41 (out of 8), which equates approximately to halfway between a B and B+. About one-quarter of the sample identified as Black or African American (24%), approximately the same number as Latino (23%), and just over one-tenth identified as Asian American (12%). Approximately one-third (34%) identified as White. Fifty-five percent of students were female, and students scored an average of 1154 points on the combined math and verbal sections of the SAT. While every student in the sample began with an interest in majoring in a STEM field, by the time four years of college were completed, 40% of students had switched majors to a non-STEM field. By the end of their fourth year in college, just over one-quarter (26%) reported majoring in biology, 20% in engineering, 8% in a health profession or health technology field, and 6% in physical sciences or mathematics.

The 224 institutions in our sample were fairly selective, with the average institutional selectivity (defined as the mean of the combined math and verbal SAT scores of the entering class) being 1107. Forty-four percent of institutions were publically controlled, 36% were research universities, and 10% could be classified as historically black colleges or universities (HBCUs). On average, STEM majors comprised approximately 16% of enrolled undergraduates, but this figure ranged from close to zero to 89%, depending on the institution.

Results from the series of hierarchical regression models are shown in Table 2. Model 1 includes only race and gender as covariates, and models 2 through 6 add academic preparation, other pre-college characteristics, student majors, college experiences, and institutional characteristics, in that order. Significant effects are indicated with an asterisk and regular typeface; non-significant effects are shown in grey type. The results of model 1 show that White students ended college with significantly higher GPAs than all other racial/ethnic groups, and that females earned higher GPAs than males. The largest difference was between White and Black students; with no other covariates in the model, we predicted that Black students would earn lower grades than White students by 1.22 points, approximately half of a letter grade on the 8-point scale used here. The difference between Latinos and Whites was next largest, with Latinos having cumulative college GPAs about 0.76 points lower than Whites. Asian American students had college GPAs approximately one-third of a point lower than Whites, and students of other race/ethnicities (a group that includes Native Americans) had cumulative college GPAs of almost half a point below their White peers. By contrast, females on average earned GPAs 0.11 points higher than males. Approximately 6.5% of the student-level variation in college students' cumulative college GPAs could be explained by race/ethnicity and gender alone.

The results of Model 2 demonstrate that a large portion of the differences in college GPAs between White students and students of non-White race/ethnicities can be attributed to differences in high school academic performance. Indeed, just over 20% of the variation in college grades can be attributed to race, gender, and high school performance. Having higher GPAs in high school and having higher SAT scores both significantly predicted higher cumulative college GPA after four years of college. Interestingly, after high school GPA and SAT scores enter the model, the coefficient for Black students dropped by half (-1.22 to -0.58), while the coefficient for Latinos dropped by approximately one-third (-0.76 to -0.41). The coefficient associated with Asian American and other race/ethnicity dropped substantially as well. These decreases in “race effects” indicate that a large portion of the discrepancy in college GPA between White students and students of other race/ethnicities can be attributed to differences in high school preparation. However, significant differences between groups in cumulative college GPAs still remained, demonstrated that even when controlling for previous achievement, non-White students tend to earn significantly lower cumulative college GPAs relative to Whites.

Model 3 adds other pre-college characteristics to the model, including an indicator of socioeconomic status, measures of students’ academic and social self-concepts, self-rated time-management skills, and a measure of the amount of time students spent studying in high school. Of these, academic self-concept and self-rated time management were both significant and positive predictors of GPA, indicating that students with higher self-efficacy in the academic arena tended to have higher GPAs after four years in college, even when controlling for high school achievement, and that students who enter college better able to manage their time effectively tend to achieve higher GPAs. The variables in this block of pre-college characteristics accounted for an additional 1.4% of variance over and above the previous block (total variance explained in model 3 was 22%).

In Model 4, students’ college majors were added in order to examine whether students who stayed in STEM or switched out of STEM reported higher grades by the end of college. Only 0.2% additional variance in student GPAs could be accounted for by students’ final major in Model 4, with students majoring in biology or health sciences having slightly higher GPAs than those majoring in non-STEM disciplines. Accounting for student major did not significantly impact the coefficients for race/ethnicity, though the significant difference between White students and “other race/ethnicity” students disappeared at this step.

In Model 5, we entered the college experience variables that our conceptual model and the literature indicate may have a significant effect on GPA, and in Model 6 we entered institutional variables. By and large, the student-level results in these two models are similar, so only the results of Model 6 are discussed in detail. Examining the differences in college GPAs by race/ethnicity, we find that accounting for college experiences and institutional characteristics eliminates the difference between Asian American students and White students, and moderates somewhat the differences between White students and Black/Latino students; however, Black and Latino students still had significantly lower predicted GPAs than White students, all else being equal. In terms of other pre-college characteristics, high school academic achievement maintained its significant positive association with college GPA after accounting for college experiences, as did self-rated time management skills and hours per week spent studying in high school. Clearly, academic and time management skills gained in high school have impacts on achievement and performance throughout college.

Student major continued to significantly predict college GPA in Model 6, although after accounting for college experiences, biology majors no longer had significantly higher GPAs than students who did not persist in a STEM major. Students majoring in health or health technology fields had significantly higher GPAs than their non-STEM peers. By contrast, after adding college experiences we found that physical science majors had significantly lower GPAs than their non-STEM counterparts—by a third of a point. This finding was surprising, given that descriptive statistics revealed physical science majors to have the highest college GPAs of any major group (6.04, compared to 5.50-5.93 for other groups). Investigating potential causes for the observed negative effect, we noticed that the coefficient for physical science and math majors becomes negative and significant after the following variables are added to the model: frequency of tutoring other students, frequency of working on a professor's research project, and participation in a structured undergraduate research program. Simple descriptive statistics revealed that physical science and math majors participate in these activities at higher rates than students of any other major, and that participation in these activities is positively related to college GPA. Therefore, it seems that physical science and math majors, relative to their non-STEM counterparts, are not earning the GPAs we would expect them to earn based on their high rates of participation in research and tutoring. That is, we would have expected physical science and math majors to have higher GPAs, on average, than we actually observe, given their high levels of research participation and tutoring other students. Put another way, if physical science or math majors maintained the same levels of tutoring and research participation, but switched their major to a non-STEM field, we would expect them to earn higher GPAs. In some ways, this provides evidence that grading in physical science and math may be harder than in other fields, which lends support to research by Barnes et al. (2001) and Rask (2010) regarding variation in grading across disciplines.

In addition to tutoring other students, working on professors' research projects, and participating in structured research programs (all of which were positively associated with college GPA for all students), many other college experience variables significantly predicted cumulative college grades, and the addition of college experiences to the model increased the proportion of level-1 variance in student GPAs explained to 34%. Not unexpectedly, the positive predictors of GPA included almost exclusively academic-related activities, such as taking honors or advanced courses, participating in programs to prepare for graduate school, discussing course content with students outside of class, and receiving faculty mentorship. However, feeling family support to succeed also significantly predicted GPA. Interestingly, there were more significant negative predictors in the model than positive ones. Some of these were socioemotional; for example, feeling overwhelmed by all one had to do was associated with lower grades, as was feeling strong competition for grades among students. Not all socioemotional variables were significant however—feeling a strong sense of belonging on campus was not associated with grades, nor was a sense that faculty are interested in students' academic problems. In terms of activities associated with lower college GPAs, taking a remedial course, receiving help with study skills from faculty, and having faculty discuss student work outside of class, were all negatively associated with cumulative college GPA.

At first the negative impacts of receiving help with study skills from faculty and discussing coursework with faculty outside of class may seem counter-intuitive because the simple correlations between college GPA and discussing coursework outside of class/receiving help with study skills are either zero (in the case of receiving help with study skills, $r = 0.006$) or positive (in the case of discussing coursework outside of class, $r = 0.130$). However, after controlling for the faculty mentorship factor, which has a strong and significant positive impact on students' GPAs, discussing coursework outside of class and receiving help with study skills both become negatively correlated with GPA—indicating that the nature of the interaction with faculty matters. It is likely that two different kinds of assistance are happening when students visit faculty to improve their study skills and/or discuss their work. In one case, students get support and encouragement from faculty; in the other they receive critical and negative feedback on their skills or work. This is not to say that negative feedback causes lower GPA, of course, rather that it predicts lower GPA. Very likely, it is the students who are not performing well to begin with who receive the negative feedback.

Three additional activities significantly and negatively predicted college grades. First, working full-time while in school negatively affected cumulative college grades, all else being equal. This effect was over and above that due to missing class because of employment, which also had a significant negative effect on college GPA. Missing class for other reasons, however, had a larger effect on cumulative GPA. Hours per week spent studying had no effect on students' grades, but hours per week spent on social networking websites like MySpace and Facebook did have an effect, and this effect was negative. To investigate whether this was an effect of spending idle time on the internet, we added a variable representing hours per week spent surfing the internet to our final model. This variable was not significant, and it did not alter the coefficient of hours per week spent social networking, so it appears that it is social networking site usage in particular that impacts GPA. Finally, participation in a racial/ethnic organization was negatively associated with GPA. It is unclear why this effect was observed; to investigate whether it was a proxy for socializing in general, we added hours per week socializing to the model. The socializing variable was not significant, and racial/ethnic organization participation maintained its significance. It is unlikely that participation in racial/ethnic student groups causes lower GPA; rather, it is likely that we are failing to account for the covariate that predicts both participation in racial/ethnic groups and lower GPAs. Future research will investigate this effect further.

In terms of institutional variables, only one significant predictor emerged: selectivity. This variable was negatively associated with average student GPAs, with more selective institutions awarding lower GPAs, on average. Interestingly, selectivity accounted—by itself—

for 52.3% of the institution-level variation in average student GPAs; the final model, including all institution-level predictors, accounted for 54.4% of this variation. Additionally, the positive level-1 effect associated with students' SAT scores increases when institutional selectivity is accounted for, indicating that, all else being equal, a student with a higher SAT score will earn a lower GPA at a higher selectivity institution than they would at one of lower selectivity.

Because Black and Latino students had significantly lower predicted college GPAs than their White counterparts, even after controlling for college experiences, we allowed the coefficients associated with these variables to vary at between institutions to determine whether the effect on college GPA of being Black or being Latino was different based on a student's institutional context. Only the coefficient for Black students displayed significant variation across institutions, indicating that differences in college GPAs between Black students and White students does vary significantly by institutional context. Unfortunately, we could not account for this variation across schools with any institutional variables, including additional variables (not in the model shown in Table 2) that represented aggregate climate indicators. Our lack of success in modeling the variation in the difference between White and Black students is intriguing and merits further inquiry in a future study.

Discussion

There are several findings from our study that merit discussion. First, for all students, entering college with stronger high school preparation in the both the academic achievement and study skills/time management arena appears to set the stage for future academic success. Similarly, participating in academic activities in college like undergraduate research programs, tutoring other students, programs to prepare for graduate school, and clubs related to academic major, also facilitate achievement. On the other hand, facing socioemotional challenges, such as feeling overwhelmed, or feeling strong competition for grades, has a negative impact on achievement, all else being equal. Interacting with faculty in a mentorship way positively impacts cumulative college grades, but receiving academic feedback outside this arena has a negative association with GPA (of course, the lower GPA may have preceded the academic feedback).

One key finding from our study is the persistent significant difference in cumulative college GPAs between White students and their Black and Latino counterparts. Accounting for students' pre-college academic preparation, college experiences, and institutional contexts reduced the predicted GPA differences between these groups by more than 60%, but there were still differences in earned grades between these groups net of students' self-efficacy, prior preparation, research experiences, and curricular and extracurricular college experiences. This finding connects to other work that has also demonstrated differences in college GPAs between White students and the Black and Latino peers (Bowen & Bok, 1998; Dennis, Phinney & Chuateco, 2005; Elmers & Pike, 1997; Roth & Bobko, 2000). Why such differences occur, even after controlling for academic background and college experiences, is perplexing. One possible explanation is that students of different race/ethnicities may derive differential benefits from college experiences (c.f. Cole, 2008, 2010; Fischer, 2007; Kim, 2006; Kim & Sax, 2009; Lundberg and Schreiner 2004). To investigate whether different groups of students do experience different impacts of similar activities, future research should either analyze models separately by race, or test for key interaction effects between racial identity and key college experiences.

Another key finding from our study is the demonstrated differences in cumulative college GPAs across students' final majors. All students in our sample entered college indending to major in STEM; four years later there were interesting differences in grades across the disciplines students actually majored in. Namely, after controlling for college experiences, we found that students who "switched out" of STEM had the same predicted cumulative college GPA as did students majoring in biology and engineering; by contrast, students who persisted in STEM and majored in health or health technology had significantly higher predicted GPAs, and those majoring in physical sciences or math had significantly lower GPAs. While this result must be interpreted with some caution, as our sample included only those students who completed at least four years of higher education and thus only those students who were academically successful enough to persist this long, the variation across students' self-reported academic major in 2008 connects to other work about the variation in disciplinary grading practices (Barnes et al., 2001; Rask, 2010).

Unfortunately, our data do not enable us to account for specific features of grading in various STEM disciplines. Examining grading within a disciplinary context would allow us to further examine why or how grading practices may vary across majors and affect students' cumulative college GPA. In future research, we plan on linking student-level data with faculty-level data to examine the impact of faculty's grading philosophy and practices on students' grades. Additionally, we plan to investigate the extent to which differences in GPAs across academic disciplines is consistent across institutions or whether these differences significantly vary based on institutional context.

Conclusion

Although we have shown that academic preparation and college experiences can account for a substantial portion of the variation in college GPA, the fact that racial disparities in cumulative college GPAs persist after controlling for these factors paints a troubling picture given the connection between GPA and students' likelihood of pursuing post-baccalaureate degrees (Mullen, Goyette, & Soares, 2003). Although we recognize the limitations of grades as a measure of students' achievement, graduate admissions offices typically have a minimum academic achievement threshold that may preclude students with lower GPAs from gaining access to these critical educational opportunities, regardless of how much they actually know. Black and Latino students, who were shown in our study to earn lower grades than equally prepared and involved White peers, likely have a lower probability of applying to and being admitted into graduate and professional programs simply because of their college GPAs. Given the calls for a more diverse scientific work force (Committee on Science, Engineering, and Public Policy, 2007) and the underrepresentation of Black, Latino, and Native American students in graduate STEM programs (Council of Graduate Schools, 2007), our inability to account for GPA differences between White students and their Black and Latino counterparts suggest that simply providing more research opportunities, studying opportunities, and mentorship from faculty may not be enough to eliminate racial disparities in college academic achievement. More research must be done to investigate the causes of achievement disparities between racial/ethnic groups, so that they can be adequately addressed.

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Table 1. *Descriptive statistics*

Variable	Mean	S.D.	Min.	Max
Dependent Variable				
Overall GPA	5.41	1.70	1.00	8.00
Demographic Characteristics				
Black	0.24	0.42	0.00	1.00
Asian American	0.12	0.32	0.00	1.00
Latino	0.23	0.42	0.00	1.00
Other	0.07	0.25	0.00	1.00
Female	0.55	0.50	0.00	1.00
Socioeconomic Status	0.00	0.90	-2.17	1.46
Pre-College Achievement				
Average High School Grade	6.58	1.42	1.00	8.00
SAT composite score (100)	11.54	1.87	5.00	16.00
Pre-College Experiences				
Academic Self-Concept - Freshman Year	-0.05	0.91	-4.35	1.46
Social Self-Concept - Freshman Year	0.03	0.81	-2.95	1.58
Hours per week spent studying in HS	4.43	1.55	1.00	8.00
Self-rated time management skills	3.28	0.90	1.00	5.00
Academic Major in 2008 (reference group: non-STEM)				
Biology	0.26	0.44	0.00	1.00
Engineering	0.20	0.40	0.00	1.00
Health and health technology	0.08	0.28	0.00	1.00
Physical sciences and mathematics	0.06	0.24	0.00	1.00
College Experiences				
Missed class due to employment	1.26	0.50	1.00	3.00
Missed class for other reasons	1.89	0.49	1.00	3.00
Tutored another college student	1.71	0.69	1.00	3.00
Worked full-time while attending school	0.22	0.42	0.00	1.00
Taken a remedial course	0.17	0.37	0.00	1.00
Participated in an ethnic/racial student organization	0.38	0.48	0.00	1.00
Enrolled in honors or advanced courses	0.34	0.47	0.00	1.00
Participated in an undergraduate research program (e.g. MARC, MBRS, REU)	0.18	0.38	0.00	1.00
Participated in a program to prepare for graduate school	0.17	0.38	0.00	1.00
Joined a club or organization related to your major	0.58	0.49	0.00	1.00
Discussed course content with students outside of class	2.65	0.53	1.00	3.00
Studied with other students	2.42	0.59	1.00	3.00
Worked on a professor's research project	1.50	0.70	1.00	3.00
Felt family support to succeed	2.50	0.65	1.00	3.00
Hours per week spent studying or doing homework	5.31	1.57	1.00	8.00
Hours per week spent on online social networks (MySpace, Facebook, etc.)	3.09	1.38	1.00	8.00
There is strong competition among most of the students for high grades	2.83	0.80	1.00	4.00
Faculty here are interested in students' academic problems	2.96	0.68	1.00	4.00
Felt overwhelmed by all I had to do	2.21	0.59	1.00	3.00
Faculty provided help to improve your study skills	1.93	0.68	1.00	3.00
Faculty provided opportunity to discuss coursework outside of class	2.29	0.65	1.00	3.00
Faculty mentorship (factor)	-0.02	0.96	-2.00	1.61
Sense of Belonging (factor)	-0.03	0.95	3.18	1.35

Table 1. *Descriptive statistics*

Variable	Mean	S.D.	Min.	Max
Institutional Characteristics				
Institutional control: Public (vs. private)	0.44	0.50	0.00	1.00
Historically Black College/University (vs. non-HBCU)	0.10	0.30	0.00	1.00
Institutional size (log)	8.55	0.95	6.00	10.51
Selectivity (in 100-point increments)	11.07	1.50	7.10	15.10
Percentage of STEM undergraduates (in 10-point increments)	1.58	1.48	0.00	8.90
Percent URM undergraduates (in 10-point increments)	2.59	2.51	0.28	9.94
University (vs. four-year college)	0.36	0.48	0.00	1.00

Table 2. *Results of hierarchical models predicting cumulative college GPA*

		Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
	Variables	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.
	Level 1																		
1	Black	-1.22	0.08	*	-0.58	0.08	*	-0.57	0.08	*	-0.56	0.08	*	-0.49	0.08	*	-0.47	0.08	*
	Asian American	-0.33	0.09	*	-0.19	0.08	*	-0.17	0.08	*	-0.21	0.08	*	-0.09	0.07		-0.09	0.07	
	Latino	-0.76	0.07	*	-0.41	0.07	*	-0.38	0.07	*	-0.38	0.07	*	-0.30	0.05	*	-0.27	0.05	*
	Other race/ethnicity	-0.45	0.13	*	-0.24	0.11	*	-0.21	0.11		-0.22	0.12		-0.18	0.11		-0.17	0.11	
	Gender (female)	0.11	0.05	*	0.15	0.05	*	0.12	0.05	*	0.07	0.05		0.11	0.05	*	0.10	0.05	*
2	HS GPA				0.35	0.03	*	0.31	0.04	*	0.30	0.04	*	0.25	0.03	*	0.27	0.03	*
	SAT Score				0.25	0.02	*	0.22	0.02	*	0.22	0.02	*	0.15	0.02	*	0.20	0.02	*
3	SES							0.03	0.03		0.03	0.03		-0.02	0.03		-0.01	0.03	
	Academic self-concept (factor)							0.11	0.03	*	0.11	0.04	*	0.05	0.04		0.03	0.04	
	Social self-concept (factor)							-0.01	0.04		-0.04	0.04		-0.05	0.04		-0.04	0.04	
	Hours per week studying in HS							-0.04	0.04		0.06	0.02	*	0.03	0.02		0.04	0.02	*
	Self-rated time management skills							0.15	0.03	*	0.15	0.03	*	0.07	0.03	*	0.07	0.03	*
4	Biology										0.20	0.07	*	-0.02	0.06		-0.05	0.06	
	Engineering										-0.05	0.09		-0.14	0.09		-0.13	0.09	
	Health sciences										0.45	0.14	*	0.36	0.13	*	0.31	0.13	*
	Physical sciences										0.06	0.11		-0.33	0.10	*	-0.33	0.10	*
5	Worked full-time while in school													-0.13	0.07		-0.15	0.07	*
	Taken a remedial course													-0.27	0.07	*	-0.27	0.07	*
	Ethnic/racial organization participation													-0.18	0.06	*	-0.15	0.06	*
	Honors or advanced courses													0.44	0.05	*	0.43	0.05	*
	Undergraduate research program													0.19	0.08	*	0.21	0.08	*
	Program to prepare for graduate school													0.15	0.06	*	0.14	0.06	*
	Club/organization related to major													0.11	0.05	*	0.09	0.05	
	Discuss courses w/ stud. out of class													0.11	0.06	*	0.11	0.05	*
	Studied with other students													-0.08	0.05		-0.08	0.05	
	Missed class due to employment													-0.12	0.05	*	-0.12	0.05	*
	Missed class for other reasons													-0.36	0.05	*	-0.36	0.05	*
	Tutored another college student													0.29	0.04	*	0.28	0.04	*
	Worked on professor's research project													0.07	0.04		0.07	0.04	
	Felt family support to succeed													0.09	0.04	*	0.08	0.04	*
	HPW Studying/homework													0.02	0.02		0.03	0.02	
	HPW Online social networks													-0.05	0.02	*	-0.04	0.02	*

Table 2. *Results of hierarchical models predicting cumulative college GPA*

	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
Variables	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.	β	SE	Sig.
Faculty provide help with study skills													-0.24	0.05	*	-0.25	0.05	*
Faculty discuss work outside of class													-0.21	0.05	*	-0.21	0.05	*
Faculty mentorship (factor)													0.44	0.05	*	0.43	0.05	*
Felt overwhelmed by all I had to do													-0.09	0.05	*	-0.09	0.05	*
Agree: Strong competition for grades													-0.16	0.04	*	-0.13	0.04	*
Agree: Faculty interested in academic problems													0.05	0.05		0.05	0.05	
Sense of belonging (factor)													0.03	0.03		0.03	0.03	
6 *Level 2*																		
Intercept	5.92	0.06	*	6.03	0.06	*	6.06	0.06	*	5.99	0.07	*	5.73	0.08	*	5.85	0.10	*
Public (vs. private)																-0.16	0.10	
University (vs. 4-year)																0.07	0.09	
HBCU (vs. non-HBCU)																-0.06	0.30	
Log(Undergraduate FTE)																0.02	0.06	
Percent URM (10-point increments)																-0.05	0.04	
Percent STEM majors (10-point increments)																-0.02	0.03	
Selectivity (100-point increments)																-0.26	0.04	*
% Level-1 variance explained	6.5%			20.6%			22.0%			22.2%			34.4%			34.4%		
% Level-2 variance explained	--			--			--			--			--			54.4%		

*indicates p-value less than .05

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Appendix A
Variables and coding

Variable	Coding
Dependent Variable	
Overall GPA	1=D to 8=A or A+
Demographic Characteristics	
Black	0=No, 1=Yes
Asian	0=No, 1=Yes
Latino	0=No, 1=Yes
Other	0=No, 1=Yes
Female	0=No, 1=Yes
Socioeconomic Status	Continuous; Factor of mother's education, father's education, and parental income (see Appendix B)
Pre-College Achievement	
Average High School Grade	1=D to 8=A or A+
SAT composite score (100-point increments)	Continuous; Range: 5.00-16.00
Pre-College Experiences	
Academic Self-Concept - Freshman Year	Continuous; Four-item factor of self-rated academic ability, math ability, writing ability, and intellectual self-confidence (see Appendix B)
Social Self-Concept - Freshman Year	Continuous; Three-item factor of self-rated social self-confidence, leadership ability, and understanding of others (see Appendix B)
Hours per week spent studying in HS	1=None to 8=Over 20
Self-rated time management skills	1=Lowest 10% to 5=Highest 10%
Academic Major in 2008 (reference group: Non-STEM)	
Biology	0=No, 1=Yes
Engineering	0=No, 1=Yes
Health and health technology	0=No, 1=Yes
Physical sciences and mathematics	0=No, 1=Yes
College Experiences	
Missed class due to employment	1=Not at all to 3=Frequently
Missed class for other reasons	1=Not at all to 3=Frequently
Tutored another college student	1=Not at all to 3=Frequently
Challenged a professor's ideas in class	1=Not at all to 3=Frequently
Worked full-time while attending school	0=No, 1=Yes
Taken a remedial course	0=No, 1=Yes
Participated in an ethnic/racial student organization	0=No, 1=Yes
Enrolled in honors or advanced courses	0=No, 1=Yes
Participated in an undergraduate research program (e.g. MARC, MBRS, REU)	0=No, 1=Yes

Appendix A
Variables and coding

Variable	Coding
Participated in a program to prepare for graduate school	0=No, 1=Yes
Joined a club or organization related to your major	0=No, 1=Yes
Studying/homework	1=None to 8=Over 20
Online social networks (MySpace, Facebook, etc.)	1=None to 8=Over 20
There is strong competition among most of the students for high grades	1=Strongly disagree to 4=Strongly agree
Faculty here are interested in students' academic problems	1=Strongly disagree to 4=Strongly agree
Felt overwhelmed by all I had to do	1=Not at all to 3=Frequently
Faculty provided help to improve your study skills	1=Not at all to 3=Frequently
Faculty provided an opportunity to discuss coursework outside of class	1=Not at all to 3=Frequently
Faculty mentorship (factor)	Continuous; Six-item factor of faculty helping achieve professional goals, providing advice/guidance about educational program, writing letter of recommendation, encouraging plans for graduate/professional school, providing feedback on academic work, and providing an opportunity to conduct research (see Appendix B)
Sense of Belonging	Continuous; Three-item factor of feeling a sense of belonging to campus, feeling like a member of the college, and seeing oneself as part of the campus community (see Appendix B)
Discussed course content with students outside of class	1=Not at all to 3=Frequently
Studied with other students	1=Not at all to 3=Frequently
Worked on a professor's research project	1=Not at all to 3=Frequently
Felt family support to succeed	1=Not at all to 3=Frequently
Institutional Characteristics	
Institutional control: Public (vs. private)	0=Private, 1=Public
Historically Black College/University (vs. non-HBCU)	0=non-HBCU, 1=HBCU
Institutional size (log)	Continuous
Selectivity (100)	Continuous; Range: 7.10-15.10
Percentage of STEM undergraduates (10)	Continuous; Range: 0.00-8.90
Percent URM undergraduates (10)	Continuous; Range: 0.28-9.94
University (vs. four-year college)	0=Four-year college; 1=University

Appendix B
Factor Items and Loadings

Factor	Item	Cronbach's Alpha	Factor Loading
Socioeconomic Status (TFS)		0.72	
	Father's education		0.83
	Mother's education		0.77
	Parental income		0.58
Faculty Mentorship (CSS)		0.88	
	Help in achieving professional goals		0.81
	Advice and guidance about educational program		0.79
	Encouragement to pursue graduate/professional study		0.72
	A letter of recommendation		0.65
	Feedback about academic work outside of grades		0.65
	An opportunity to work on a research project		0.60
Sense of Belonging (CSS)		0.68	
	I feel I have a sense of belonging to this campus		0.87
	I feel I am a member of this college		0.85
	I see myself as part of the campus community		0.79
Entering Academic Self-Concept (TFS)		0.59	
	Academic ability		0.87
	Self-confidence (intellectual)		0.54
	Mathematical Ability		0.47
	Writing ability		0.37
Entering Social Self-Concept (TFS)		0.61	
	Self-Confidence (social)		0.69
	Leadership ability		0.66
	Understanding of others		0.38