Predicting Undergraduates' Persistence in Science, Technology, Engineering, and Math Fields

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Abstract

A national shortage of workers in Science, Technology, Engineering, and Math (STEM) occupations has led to efforts to identify why people leave these fields. Lower persistence rates in STEM for females than for males have also led to examinations of features that cause females to leave STEM fields. The current study examines individual- and school-level features that influence undergraduate students' decisions to leave STEM majors, focusing on potential explanations for why females are more likely than males to leave. Persistence in STEM was examined in three samples: (a) persistence through the second year of college in a sample of high school seniors interested in STEM majors; (b) persistence through the fourth year of college in a sample of second year undergraduate STEM majors; and (c) persistence through the second, third, and fourth years of college in a sample of high school seniors interested in STEM majors. Differences between persistence in male-dominated and non-male-dominated STEM majors were also examined. In all samples, gender differences were found for most individual-level predictors, with males tending to score higher than females on measures such as SAT-Math, self-rated STEM ability, and high school extracurricular activities and awards in STEM. On the other hand, females earned better high school grades and had stronger relative non-STEM ability and achievement than males. Bivariate analyses indicated that those who persisted in STEM majors typically had higher scores than those who did not persist for SAT-Math, high school achievement, STEM course taking, undergraduate STEM grades, self-rated STEM ability, interest in STEM, extracurricular activities and awards in STEM, degree goals, and socioeconomic status. Multivariate analyses

identified SAT-Math as one of the best predictors of persistence in high school samples, and undergraduate STEM GPA was one of the best predictors in the samples of second year undergraduates. In several samples, a significant cross-level interaction was found between gender and undergraduate females' college-level proportional representation in STEM; however, the effects were inconsistent across samples. Even when controlling for various individual- and school-level predictors, gender effects tended to remain significant, with females in most samples leaving STEM majors at higher rates than males.

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INTRODUCTION

The importance of Science, Technology, Engineering, and Mathematics (STEM) fields and the U.S.'s shortcomings in these fields have received much attention, and concerns persist regarding the country's ability to produce the desired quantity and quality of STEM professionals. For example, a committee convened by the National Academy of Sciences (2007) noted:

> The United States still leads the world in many areas of science and technology, and it continues to increase spending and output. But our share of world output is declining, largely because other nations are increasing production faster than we are….The biggest concern is that our competitive advantage, our success in global markets, our economic growth, and our standard of living all depend on maintaining a leading position in science, technology, and innovation. As that lead shrinks, we risk losing the advantages on which our economy depends. (p. 218)

Similarly, a report from the Office of the Director of National Intelligence (2011) stated:

> The engines of our country – innovation, economic competitiveness, national security, and a strong and agile military – are dependent on the application of STEM; the last 50 years have seen more advancement in STEM-related fields than in any other period in history. Yet the U.S. is falling behind. (p. 3)

There is some evidence indicating reason for concern. The number of Americans employed in STEM occupations has been growing in recent years, and it is projected that this number will continue to grow (President's Council of Advisors on Science and Technology, 2012). Some anticipate that the number of jobs in STEM occupations will increase at a higher rate than any other occupation (see Tyson, Lee, Borman, & Hanson, 2007). In projections through 2018 of job openings in STEM and the educational requirements of those jobs, it has been estimated that 44 percent of projected openings in STEM jobs will require a bachelor's degree; additionally, 28 percent of STEM openings will require a graduate degree, which is likely preceded by a bachelor's degree in a STEM field (President's Council of Advisors on Science and Technology, 2012).

However, the supply of qualified workers with bachelor's degrees in STEM fields may not be able to meet this growing demand. Although the total number of bachelor's degrees awarded in the U.S. has been increasing in recent decades, the proportion of undergraduates earning STEM degrees has decreased (Green, 1989; President's Council of Advisors on Science and Technology, 2012). The number of students earning bachelor's degrees in engineering, math, or computer sciences was higher in 1985 than in 2000 (National Academy of Sciences, 2007), and the number of bachelor's degrees awarded in biological sciences and physical sciences was higher in 1997 than in 2002 (Goan & Cunningham, 2006). Compared to undergraduate students in some other countries, undergraduates in the U.S. are much less likely to earn degrees in STEM fields. For example, 50 percent of all undergraduates in China and 67 percent of undergraduates in Singapore earn their degrees in natural science or engineering fields, compared to only 15 percent of undergraduates in the U.S. (National Academy of Sciences, 2007). As a reflection of this shortage, the federal government identifies occupations that are "areas of national need" that are critical to "national innovation, competitiveness, and well-being and in which not enough students complete degrees" (Goan & Cunningham, 2006, p. 1). Included on this list of high demand fields are several core STEM fields: physical sciences, biological sciences, computer and information sciences, engineering and engineering-related technologies, and mathematics (Goan & Cunningham, 2006).

Thus, there is clearly interest in increasing the number of qualified STEM professionals in the U.S., with some suggestions that at current rates of degree attainment in STEM fields, supply will be markedly short of meeting demand in the coming years. Due to heavy "leaks" in the STEM pipeline during college, the present study focuses on persistence in STEM fields during college among those who show interest in pursuing a STEM career. Because careers in most STEM fields require post-secondary training, examining the post-secondary pipeline that feeds into the STEM workforce can provide insight into why the shortage of STEM professionals exists. In the present study, I explore this issue by examining factors that influence undergraduate students' persistence in STEM majors.

Although previous research has approached the issue of STEM persistence from different theoretical perspectives (e.g., decision making theories, self-efficacy theories) and has identified various predictors that are important in predicting persistence in STEM majors (e.g., ability, interest, achievement), several issues remain. First, many researchers have focused on a small set of variables or a single theory to examine the issue of STEM persistence (e.g., Tyson et al., 2007). Most have not considered both individual- and college-level features that may influence persistence, tending to focus only on individual-level variables. Others have examined only bivariate relationships, leading to a lack of clarity about which variables best predict STEM persistence when the effects of multiple predictors are examined simultaneously (e.g., Chen & Weko, 2009). Analyses are often cross-sectional, and samples are not often representative (see Xie & Shauman, 2003).

The present study addresses these issues and contributes to the literature in several important ways. By including a variety of variables representing various theoretical perspectives and exploring their simultaneous effects, the current research provides a more comprehensive view of critical predictors of STEM persistence. Both individual- and college-level effects are included in a multilevel modeling framework, allowing for the identification of important predictors of STEM persistence that have not previously been studied together. The sample represents a variety of colleges that were selected according to a sampling plan to be diverse on various characteristics, allowing for increased confidence in the generalizability of findings. Finally, the current research's unique longitudinal nature allows for the study of STEM persistence over time, including identifying how predictors may vary in importance at different time points during college, a rarely addressed issue. To summarize, the present study examines an array of individual- and college-level predictors of STEM persistence, including ability, achievement, interest, self-rated ability, educational goals, college selectivity, and college-level female representation in STEM. This collection of predictors was measured at multiple time points during high school and college for over 25,000 undergraduates at nearly 100 four-year colleges and universities in the U.S., allowing the study to address key questions that remain in this literature.

The STEM "Pipeline"

Many have attributed the shortage in the supply of STEM workers to high attrition from the STEM talent pool or "pipeline" that can be thought of as "a structured set of educational stages that comprise a science career," starting with "the sequence of college-track math and sciences courses in middle and high school, followed by science concentration in undergraduate college, science graduate study, and/or employment in a science occupation" (Xie & Shauman, 2003, p. 7). The "leaky pipeline," or the loss of students somewhere along the path to a STEM career, has been a focus for many, including during the undergraduate years. For example, in a large, nationally representative sample, Chen and Weko (2009) found that among first year undergraduates intending to major in a STEM field, more than half had not earned a STEM degree six years later. In a large-scale study with thousands of American college students, Astin and Astin (1992) found that undergraduates were more likely to leave STEM majors than they were to leave other majors during their undergraduate careers. Astin and Astin also found that entering college freshmen who intended to major in biological or physical sciences were more likely to obtain a degree in a non-science field than they were to remain in the biological or physical sciences.

Furthermore, others have noted that from sophomore year of high school all the way through graduate school, the loss of students from the STEM pipeline is greater than the gain; at each educational transition point, there are more students leaving STEM than there are students entering STEM, leading to a net loss (Hilton & Lee, 1988). Although it is common to switch into certain majors during college, it is relatively rare to switch from a non-STEM to a STEM major (Hilton & Lee, 1988; Seymour, 2001). As Hilton and Lee (1998) put it, "At later stops in the educational pipeline, science attracts few newcomers and mainly battles to hold old adherents" (p. 523). This makes persistence among those who show early interest in STEM fields even more important for fulfilling future demand for STEM professionals. The President's Council of Advisors on Science and Technology, an advisory group appointed by the president to make policy recommendations, has provided economic forecasts estimating that a shortage of approximately one million college graduates with STEM degrees will accrue during the next decade if current educational trends continue (2012). The President's Council of Advisors on Science and Technology also reported that meeting the demand for STEM workers would require the number of students receiving bachelor's degrees in STEM to increase by approximately 34 percent annually over current rates.

Underrepresentation of Women

In addition to the shortage of STEM professionals in general, the underrepresentation of women compared to men in STEM fields, given their education levels, is another popular topic. Among all those in the U.S. who are college-educated and employed full-time, one in three men but only one in seven women works in a STEM occupation (Graham & Smith, 2005). Even more troubling is that the STEM occupations expected to have the largest growth and need for employees, computer specialists and engineers, are also areas in which women are heavily underrepresented; women comprise only 13 percent of engineers and 27 percent of employees in computer-related occupations (President's Council of Advisors on Science and Technology, 2012). Many have noted that if the U.S. is going to produce enough STEM professionals to meet increasing demands, the number of women in STEM occupations will need to increase (e.g., National Academy of Sciences, 2007; Office of the Director of National Intelligence, 2011). Various initiatives have been implemented to address the lack of women in STEM fields. For instance, the National Science Foundation's ADVANCE program was designed to "increase the representation and advancement of women in academic science and engineering careers, thereby developing a more diverse science and engineering workforce" and has invested 135 million dollars into programs at colleges, universities, and non-profit organizations to further this goal (National Science Foundation, 2009, p. 1). Although women's representation in the STEM workforce has increased over time, women remain severely underrepresented in many STEM occupations, compared to men. For example, women held fewer than 1 percent of engineering jobs in 1960, a figure that increased to nearly 11 percent in 2000 (Hill, Corbett, & St. Rose, 2010).

Similarly, although there is an overall shortage of undergraduates earning STEM degrees, the shortage of women is more extreme. Women are more likely than men to earn college degrees, earning 58 percent of all bachelor's degrees in the U.S. (National Science Foundation, 2008), yet more than twice as many college-going men than women choose a STEM degree at some point during their college careers (Chen & Weko, 2009). Among those who entered college in the U.S. in 2003, 21 percent of men enrolled in a STEM major, but only 6 percent of women chose a STEM major (President's Council of Advisors on Science and Technology, 2012). Women remain underrepresented in most

STEM fields at all post-secondary education levels, including the attainment of associate's, bachelor's, master's, and doctoral degrees, as well as in faculty positions (Glass & Minnotte, 2010; Goan & Cunningham, 2006).

In addition to entering the STEM pipeline at lower rates than men, women have been found to leave the STEM pipeline at various time points at higher rates than men. Among high school students interested in pursuing math and science careers, a larger proportion of males than females persist (Farmer, Wardrop, Anderson, & Risinger, 1995). Even when controlling for other relevant individual difference variables, some find that women are still less likely than men to persist in STEM majors during college, particularly for majors in which women are underrepresented (e.g., Ost, 2010). Understanding why women leave STEM fields at higher rates than men is important, especially considering the relatively small number of women who enter the STEM pipeline to begin with. In the present study, I explore several proposed explanations for gender differences in STEM persistence, including variables that reflect ability, academic preparation and investment, achievement, self-rated ability, interests, and educational goals, all of which are expected to be associated with persistence in STEM majors.

Hypothesis 1: Males will persist in STEM majors at higher rates than females.

Theoretical Perspectives on Predicting Career Choices

Various theories related to vocational choice attempt to explain why people choose to enter or remain in certain occupations and may be relevant to students' persistence in STEM fields. These include theories that address individuals' decision making, environmental influences, and congruence between individuals and the environment. When considered together, these theories suggest a variety of individual and environmental characteristics that likely influence students' persistence in STEM fields.

Decision making theories (e.g., expectancy theory, Vroom, 1964; decision theory, see Mitchell & Beach, 1976) tend to focus on alternative courses of action available to the decision maker (e.g., different college major options), the likelihood of attaining each course of action (e.g., the perceived likelihood of earning a degree in a particular major), the probability that particular outcomes will occur with each possible course of action (e.g., likelihood of attaining a high paying job after earning a degree in a particular field), and the value or importance of these outcomes for the decision maker (e.g., the extent to which the decision maker values a high salary). Using this information, the decision maker considers alternatives, selects the most valuable course of action, and commits to the choice. When considering college majors, students likely make judgments about their ability to complete a degree in a major and the likelihood of attaining valued outcomes with a degree in that major. Similarly, an expansion of Bandura's (1982) self-efficacy theory, social cognitive career theory (Hackett & Betz, 1981), posits that self-efficacy, or "beliefs in one's ability to successfully perform particular behaviors or courses of action," and outcome expectations predict occupational interests, which in turn predict career choices (Sheu, Lent, Brown, Miller, Hennessy, & Duffy, 2010, p. 253). Hackett and Betz (1981) hypothesized that four sources of information affect students' career-related self-efficacy: (a) performance accomplishments, (b) vicarious learning, (c) emotional arousal, and (d) verbal persuasion. For example, prior success or positive feedback in a domain, such as excellent grades, may encourage persistence in the domain.

Various other personal characteristics and behaviors may also influence students' assessments of their likelihood of attaining a particular degree and the value they place on certain outcomes. For example, Fassinger's model of career choice identifies three personal factors that are posited to affect career choice: (a) ability, which has been operationalized as high school GPA, ACT scores, and number of high school math courses taken; (b) agentic characteristics, which have been operationalized as independence, assertiveness, and ambition; and (c) career orientation, which has been operationalized as the importance of one's career, attitudes toward work, and the relative importance of family versus career (Fassinger, 1990; O'Brien & Fassinger, 1993). Whereas ability and agentic characteristics may influence students' perceived probability of successfully earning a degree in an area (e.g., those with high domain-relevant abilities should believe that success in the domain is more likely than do those with low domain-relevant abilities), career orientation may influence the value they place on particular outcomes (e.g., those who place a higher value on family satisfaction than career satisfaction may be less interested in occupations perceived as requiring the largest time investment). These theoretical perspectives on career-related decision making lead to the prediction that a variety of individual characteristics, such as ability, prior exposure to and success in a domain, self-efficacy, and interest, will impact a student's choice to pursue a STEM career.

Other research identifies environmental features, such as socialization and societal forces, that influence career choices. Astin (1984) cited the importance of societal values and expectations for males and females that shape their interests and perceptions of the appropriateness of particular careers. Others focus on more proximal contextual factors in educational or occupational systems that deter women from pursuing or persisting in traditionally male-dominated fields. For instance, the "chilly climate hypothesis" (see Strenta, Elliott, Adair, Matier, & Scott, 1994) posits that various types of intentional or unintentional discrimination (e.g., overt gender bias, disrespect, lower expectations for women) as well as structural features of male-dominated domains (e.g., fewer same-sex role models for women, competitive environments that are less appealing to women) help to explain higher attrition rates for women compared to men. Kanter's (1977) research points to the difficulties faced by group members whose proportional representation in a setting is low. An environment without a "critical mass" of women can lead to increased stereotyping, exaggerations of group differences, reduced social networks or mentoring, or bias in evaluations or decision making (see also Etzkowitz, Kemelgor, Neuschatz, Uzzi, & Alonzo, 1994). Thus, the pressures faced by women in male-dominated environments, a feature of many STEM fields, can be expected to lead to greater attrition for women than men (Kanter, 1977).

Most researchers recognize that individual attributes and behaviors as well as contextual variables play a role in occupational choices. For example, Farmer et al. (1995) identified four categories of variables that influence choice to persist in STEM fields: (a) demographic, such as gender, race, and SES; (b) cognitive, such as self-efficacy, career aspirations, and beliefs about the utility of math and science; (c) behavioral, such as high school course taking; and (d) environmental, such as support from parents, teachers, or society. Some theories focus explicitly on the fit or congruence between personal characteristics such as abilities, values, needs, or work styles and the environment's characteristics. For example, the theory of work adjustment (Dawis & Lofquist, 1976; Rounds, Dawis, & Lofquist, 1987) predicts that individuals will be satisfied when the work environment's reinforcer pattern fulfills their needs and when their abilities are congruent with job demands, leading to increased tenure, among other outcomes. Holland's (1959) theory of vocational choice highlights the importance of the fit between a person's vocational personality or interests and the environment. Similarly, an attraction-selection-attrition (ASA, Schneider, 1987) viewpoint leads to several predictions: (a) people will be attracted to careers or majors that align with their interests, abilities, or personalities; (b) decision makers will select and retain individuals whose characteristics are consistent with those in the occupation or organization; and (c) students whose characteristics do not align well with the environment will leave that environment. From an ASA perspective in the context of majoring in a STEM field, it is expected that certain types of students are attracted to STEM majors, are admitted into STEM programs, and find the environment within STEM departments satisfying, leading to their persistence in STEM. Individual characteristics that may be associated with attraction to and retention in STEM could include domain-relevant experience, ability, and interest.

The theoretical perspectives discussed thus far offer a broad framework for studying the issue of STEM persistence. Because students' career decisions depend on their judgments about the attainability of various majors, their decision to pursue and persist in STEM is expected to be related to their STEM-relevant abilities, STEM self-efficacy, and prior successes and failures in STEM. Similarly, theories addressing person-environment fit or congruence lead to the prediction that students with high STEM-relevant abilities and interests (i.e., those whose abilities and interests fit with the environment) will be more likely to persist in STEM than those with lower STEM-relevant abilities and interests. Finally, because certain environmental features can create barriers to persistence, particularly for underrepresented groups, college-level features such as female representation in STEM are expected to influence STEM persistence.

A variety of explanations have been proposed for poor persistence rates of students, particularly females, in the STEM pipeline, and the present study explores several of these. It is expected that the choice to persist in STEM majors during college will be influenced by personal characteristics and behaviors including abilities, achievement, course taking, self-rated ability, interests, educational goals, demographic variables, and contextual variables including college characteristics, classmate characteristics, and females' proportional representation in college STEM departments. In the following sections, I discuss each of the variables that are used in the present study to predict retention in STEM fields. For each potential predictor, I describe (a) previous findings on gender differences for the predictor, both in nationally representative samples and in samples restricted to students with interest in STEM fields, as these findings may provide explanations for women's underrepresentation in STEM fields; (b) prior research providing evidence about its prediction of both selecting a STEM major (in nationally representative samples) and of remaining in a STEM major (in samples restricted to those with interest in STEM fields); and (c) relevant theories and potential explanations that inform hypotheses.

Ability and Achievement Tests

Gender differences. Meta-analytic evidence and nationally representative studies (e.g., National Assessment of Educational Progress; National Education Longitudinal Study of 1988) indicate that for many math and science ability and achievement tests in middle and high school, males tend to score higher than females and are more likely than females to score at the highest performance levels (Huang, Taddese, & Walter, 2000; Kahle, 1996). The magnitude of mean gender differences has been found to range from near zero to approximately three-fourths of a standard deviation and depends on moderators such as the age of participants, type of test, and year of study (e.g., Friedman, 1989). Gender differences in math ability and achievement often increase from elementary to middle to high school age samples (Friedman, 1989). Male-female differences are more likely to be found for certain math skills such as spatial visualization, mechanical reasoning, and quantitative reasoning and for particular science fields such as physics (see Lubinski & Benbow, 1992; Xie & Shauman, 2003). However, overall mean gender differences are often small and have gotten smaller in recent years (see Friedman, 1989; Lauzon, 2001). Nevertheless, greater variability of scores for males than for females in math and science domains (see Huang et al., 2000; Lauzon, 2001; Xie

& Shauman, 2003) indicates that more males than females score in the upper tail of the distribution, and gender differences are still found in selective, high ability samples (see Lubinski & Benbow, 1992). Lubinski and Benbow (1992) pointed out that “a greater number of males than females will qualify for advanced training in disciplines that place a premium on mathematical reasoning” (p. 62). This is an important consideration, given the math ability required for most STEM professions and the relationship between math ability and attainment of a STEM degree.

Although it has been established that in nationally representative samples males tend to score higher and have more variability than females on math and science ability and achievement tests, evidence on gender differences in samples of students who indicate interest in STEM is sparser. There is some evidence indicating that the same pattern of gender difference holds in these samples. For example, using a subsample of the nationally representative, longitudinal High School & Beyond sample that included high school seniors who scored above the 50^{th} percentile on an achievement test and had declared a STEM major in college two years later, Ware and Lee (1988) found that males had higher high school math achievement scores than females. Similarly, both Smyth and McArdle (2004) and Strenta et al. (1994) found that in samples of students entering selective universities and intending to major in STEM fields, males earned higher SAT-Math scores than did females. It is expected that in the present study, which includes samples of students interested in STEM majors, males will score higher than females on a math ability measure.

Gender differences in math and science abilities sometimes evoke biological explanations (e.g., differences in brain structure or hormones, see Hill et al., 2010). Others focus on environmental or socialization factors that may lead to gender differences. For example, gender differences in encouragement, attention, interactions, and expectations from teachers and parents have been suggested as potential environmental causes of math and science ability gender gaps (see Lauzon, 2001). Some point to relatively rapid decreases in the gender gap in math and science ability tests as an indicator that environmental features and interventions are critical (Valian, 2006). For example, Hill et al. (2010) stated:

> The rapid increase in the number of girls achieving very high scores on mathematics tests once thought to measure innate ability suggests that cultural factors are at work….This increase in the number of girls identified as 'mathematically gifted' suggests that education can and does make a difference at the highest levels of mathematical achievement. (p. xiv)

Many of the factors discussed later in this section, such as gender differences in interests, self-rated ability, or course taking, may contribute to the ability/achievement gender gap, though the relationships are likely reciprocal (e.g., students with high math achievement continue to take math courses, which feeds into high math achievement test scores).

Hypothesis 2: Males will earn higher SAT-Math scores than females.

Prediction of entering or remaining in a STEM field. Existing research suggests that abilities in math and science are important predictors of choosing and persisting in a STEM major. Numerous researchers studying middle and high school students' decisions to choose STEM majors in college have found that math and science ability and achievement test scores are significant predictors of selecting STEM majors. For instance, SAT-Math scores predict choosing a STEM major during freshman year of college as well as completing a degree in a STEM field (e.g., Astin & Astin, 1992; Astin & Sax, 1996; Strenta et al., 1994), and math achievement test scores from as early as eighth grade predict STEM degree attainment (Tai, Liu, Maltese, & Fan, 2006).

Math and science ability and achievement tests also predict persistence among those who choose STEM majors. For example, Nauta and Epperson (2003) found that in a sample of high school girls who indicated interest in STEM, ACT Math and Scientific Reasoning scores predicted majoring in a STEM field during college. In samples of students who enter college with the intention of majoring in a STEM field, SAT-Math score has been found to be a significant predictor of earning a STEM degree (Dickson, 2010; Ost, 2010; Smyth & McArdle, 2004). Therefore, in the present study, it is expected that a math ability measure will predict persistence for samples of students interested in STEM majors.

Most theories of career choice acknowledge that individuals' abilities play a role in career selection and persistence. People who lack sufficient domain-relevant abilities will likely have difficulty being successful in the domain, and as a result may end up failing or becoming dissatisfied and switching to a domain where their abilities are more compatible with demands (Dawis & Lofquist, 1976). Scores on math or science ability/achievement tests also may deter some from attempting to enter the STEM pipeline due to their impact on self-efficacy or expectations of success (e.g., success in STEM is viewed as unlikely). Even if other factors such as high interests and goals are present, these factors may not be able to compensate for low ability; therefore, STEM-related ability is expected to predict STEM persistence in both bivariate and multivariate models.

Hypothesis 3: SAT-Math scores will be positively related to persistence in STEM majors.

Course Grades

Gender differences. The gender gap found for math and science ability/achievement tests (i.e., males outscoring females) is typically reversed for high school grades, with females outperforming males in high school courses, including math and science courses (Goldin, Katz, & Kuziemko, 2006; Sax, 2008; Xie & Shauman, 2003). The magnitude of this effect varies, but in a recent study by Mattern and Patterson (2012) that included several hundred thousand college students at nearly 200 universities, females' high school GPAs were .19 standard deviations higher than males'. These gender differences have also been found in more selective samples. For instance, in a longitudinal study with a sample of middle school students who scored above the 95th percentile in math ability, Benbow and Stanley (1982) found that although the males in this talented group scored higher than females on math ability and achievement tests during high school, females reported receiving higher math grades than males. This research leads to the expectation that females will earn better high school grades than males. When examining overall college GPA across samples of undergraduates with various majors, this pattern tends to hold, with women earning higher college GPAs than men (e.g., $d = .23$; Mattern & Patterson, 2012).

Research on gender differences in academic engagement and course taking patterns can help to explain why males tend to have higher math and science ability scores whereas females tend to have higher math and science grades. From a young age, females are more likely than males to demonstrate a variety of academic behaviors associated with school achievement. For example, in a national sample, Huang et al. (2000) found that females were significantly more likely than males to report completing their science and math homework in 8th, 10th, and 12th grades. Additionally, females are more likely than males to report that they work hard at math and science classes in middle and high school (Catsambis, 1994; Deboer, 1986), and high school teachers report that girls are more likely than boys to work hard at school, to be attentive during class, and to complete homework (Downey & Yuan, 2005). Not surprisingly, these behaviors continue into college. Pryor, Hurtado, DeAngelo, Blake, and Tran (2009) asked a large sample of college freshmen about the behaviors they had engaged in during the previous year and found that females were more likely than males to (a) spend 6 or more hours per week on studying/homework (40 percent of females versus 29 percent of males), (b) ask teachers for advice after class (30 percent of females versus 24 percent of males), (c) ask questions during class (57 percent of females versus 50 percent of males), (d) revise papers to improve their writing (55 percent of females versus 37 percent of males), (e) take notes during class (79 percent of females versus 52 percent of males), (f) seek feedback on their academic work (53 percent of females versus 40 percent of males), and

(g) work with other students on class assignments (60 percent of females versus 48 percent of males). Other studies in multiple institutions have indicated that during college, men spend less time studying, are less likely to finish homework assignments, are more likely to procrastinate or cram at the last minute, have worse course attendance, spend less time talking to instructors, and are less likely to seek help with their studies when they need it, compared to women (Sax, 2008; Strenta et al., 1994; Vogt, Hocevar, & Hagedorn, 2007). Given the gender differences on a variety of behaviors that contribute to school performance, it does not seem surprising that females earn higher grades than males in high school and college.

Another line of research that sheds light on the topic of gender differences in college grades is related to gender differences in course taking. More males than females choose college majors with harsher grading standards, including many STEM fields, and gender differences in GPAs are often reduced when course taking patterns are taken into account (Beatty & Sackett, 2009; Ost, 2010; Pennock-Román, 1994). A few studies have examined major-specific college GPAs in samples of STEM majors. For example, in a sample of students entering four selective colleges and intending to major in STEM fields, Strenta et al. (1994) found that males earned higher GPAs in STEM courses during their first two years of college than did females. In a single-institution sample of chemical engineers, Felder, Felder, Mauney, Hamrin, and Dietz (1995) found that men's and women's grades in introductory math and science courses did not differ, but men earned higher grades than women in major-specific courses. Thus, although females earn higher high school GPAs and overall college GPAs than males, this advantage may be eliminated or reversed when examining only grades in college STEM courses in samples of STEM majors. It may be that among STEM majors, who tend to be a more academically able group than students in other majors (e.g., higher grades in high school and higher entrance exam scores, Astin & Sax, 1996; Strenta et al., 1994), the typical gender differences in responsible school-related behaviors (e.g., finishing assignments, attending class, effort) are smaller than in the broader college-going population. STEM majors may be a more motivated, hard working group in general, which may reduce the female grade advantage in these selective samples. Because prior research indicates that even in samples of students interested in STEM majors, females earn higher high school GPAs than males, I expect females in the present study to have higher high school achievement (i.e., grades and class rank) than males. Due to mixed findings regarding gender differences in college STEM course grades, I do not have a hypothesis regarding gender differences in college STEM grades.

In addition to the finding that males and females have different academic behaviors and grades, some prior research indicates that males and females may react differently to the grades they earn. Felder et al. (1995) found that when students experienced failure in their college classes, women were more likely than men to attribute their failures to lack of ability. Men were more likely than women to attribute their success to their ability, whereas women were more likely to attribute their success to help or support from others. Similarly, in a single-institution sample of college students who indicated interest in majoring in a STEM field, Ware, Steckler, and Leserman (1985) found that when asked why their most difficult course had been so difficult, women were more likely to attribute their difficulties to their own inadequacies (e.g., inability to understand math), whereas men were more likely to attribute their difficulties to external factors (e.g., poor teaching). These findings suggest that there may be an interaction between gender and college grades in the prediction of STEM persistence. If women are more likely than men to attribute failures to their lack of ability, women may be less likely to persist in STEM after experiencing failure (e.g., poor STEM grades lead to the conclusion that one is not capable in the domain). On the other hand, men, who are more likely to attribute their failures to external characteristics, may be more likely than women to persist in STEM following a failure (e.g., poor STEM grades do not strongly affect the perception of one's ability to succeed in the domain). Therefore, I expect to find an interaction between gender and college STEM grades, with the gap between males' and females' persistence in STEM predicted to be largest among those who earn poor STEM grades during college.

Hypothesis 4: Females will earn better high school grades than males.

Hypothesis 5: Gender will interact with college STEM grades in the prediction of STEM persistence, such that males' and females' persistence rates will be most different among those who earn poor STEM grades during college.

Prediction of entering or remaining in a STEM field. Researchers studying large, national samples have found that high school course grades and high school class rank predict the selection of a STEM major during the early years of college as well as the completion of a degree in a STEM field (Astin & Astin, 1992; Astin & Sax, 1996; Leslie, McClure, & Oaxaca, 1998; Maltese & Tai, 2011; Ware & Lee, 1988). Those examining high school grades in math and science courses in particular have reported similar results. For example, in a sample of students entering four selective colleges, Strenta et al. (1994) found that freshmen interested in science majors had earned higher grades in high school math and science courses than students interested in non-science majors.

In samples of students already in the STEM pipeline (i.e., majoring in or intending to major in STEM), grades tend to remain an important predictor of STEM persistence. In multiple-school studies, both Dickson (2010) and Smyth and McArdle (2004) reported that among students intending to major in STEM, high school GPA was a significant predictor of earning a STEM degree. Chen and Weko (2009) found that in a sample of first year college students intending to major in STEM, those with a high school GPA of a B average or higher were nearly twice as likely as those with below-B high school GPAs to earn a STEM degree six years later. Using high school science grades rather than overall high school GPA, Gayles and Ampaw (2011) found that high school science GPA was the best predictor of attaining a STEM degree among college students who had declared a STEM major (other predictors included demographic, high school preparation, and institutional variables). Similarly, college grades appear to be an important predictor of persistence in STEM majors. Various researchers have found that among students intending to major in STEM, both overall college GPA and college STEM GPA predict persistence and completion of a degree in STEM (Gayles & Ampaw, 2011; Maltese & Tai, 2011; Ost, 2010; Schaefers, Epperson, & Nauta, 1997; Strenta et al., 1994). Even when controlling for other measures of ability, self-efficacy, interest, and environmental variables, undergraduate STEM grades remain a significant predictor of retention in STEM majors (Maltese & Tai, 2011; Schaefers et al., 1997). Therefore, course grades in both high school and college are expected to be important predictors of persistence in STEM majors.

As measures of performance, grades indicate whether students have successfully met the course-related demands placed on them. Poor grades can be viewed by individuals as evidence of failure, which may lower self-efficacy, particularly if the outcome did not result from a lack of effort or adverse environmental circumstances, and those with low self-efficacy are less likely to continue to put forth effort in the domain (Bandura, 1982). Conversely, high grades in a domain may increase both self-efficacy in that domain and one's willingness to persist in it. Poor grades can also indicate that individuals' abilities are not congruent with demands, leading them to be dissatisfied and to choose a different environment (e.g., Dawis & Lofquist, 1976; Rounds et al., 1987). Students may also consider college grades to be indicators of the likelihood of earning a degree in the field, so early course grades may cause them to reevaluate their major choice based on expected future outcomes. Additionally, grades are used by colleges for decision making, so poor grades may cause students to leave STEM majors even if they do not want to (e.g., a college may require a student's early college GPA to be above a certain threshold for the student to be admitted into their desired STEM major). Even when controlling for other features such as interest or domain-relevant experiences, course grades are likely to play a role in students' persistence in STEM; poor grades may deter students from continuing either because of their own reactions or because of decisions made by others. Therefore, grades are expected to influence persistence in STEM in both bivariate and multivariate analyses.

> *Hypothesis 6*: High school grades will be positively associated with persistence in STEM majors.
>
> *Hypothesis 7*: College STEM grades will be positively related to persistence in STEM majors.

Course Taking

Gender differences. A popular explanation for women's underrepresentation in STEM fields is that men are more likely to have the appropriate high school preparation for college STEM courses. Until the early 1970s, gender differences in science and math course taking in high school were large; however, in subsequent decades, this gender gap has become smaller, with women taking increasingly more math and science courses during high school (Goldin et al., 2006). Recent studies conducted with nationally representative samples suggest that males' and females' math course taking during the early years of high school has become quite similar, but some researchers have reported that males are still more likely than females to take advanced math and science classes such as calculus and physics during their final years of high school (Catsambis, 1994; Federman, 2007; Ma & Johnson, 2008; Xie & Shauman, 2003). On the other hand, more females than males take advanced high school biology courses (National Academy of Sciences, 2007). Similarly, more male than female high school students take most STEM Advanced Placement (AP) tests, specifically in calculus, chemistry, physics, and computer science, whereas more females than males take the biology and environmental science AP tests (Hill et al., 2010; Strenta et al., 1994). Males' average scores on each of these AP tests are equal to or higher than females' average scores, though the gender differences vary by subject (Hill et al., 2010). Some have pointed to early elementary or middle school course taking as one of the causes of gender differences in high school course taking. For example, in a national sample of eighth grade students, more males than females reported being placed in a high ability group for math or science, and those in a high ability track are likely to be better prepared for high school math and science classes (Huang et al., 2000). However, gender differences have been found even in high ability groups. In Benbow and Stanley's (1982) sample of mathematically gifted adolescents, males took more high school math courses than did females, suggesting that non-cognitive factors such as interest play an important role.

When research is conducted with samples of students indicating interest in pursuing a STEM career, results regarding gender differences in course taking tend to be mixed. Some have found that, like in nationally representative samples, males tend to take more high school math and science courses than females. For instance, in the nationally representative, longitudinal High School & Beyond sample, Ware and Lee (1988) found that among STEM majors with above average ability, males had taken more high school math and science classes than females. Similarly, in a study of freshmen computer science majors at a selective university, Margolis, Fisher, and Miller (2000) reported that 40 percent of males had taken and passed the AP computer science exam during high school, whereas none of the females had done so. However, others have found that course taking does not differ between males and females in samples of STEM majors. For example, Farmer et al. (1995) found no significant gender differences in high school science course taking in their sample of 9th and 12th graders showing interest in a STEM career, leading them to suggest that although men may take science courses more routinely in high school, women who are motivated to pursue a career in science do not differ from males in science course taking. Due to the differences in findings of previous research, it is not clear whether gender differences in STEM course taking in high school should be expected. Gender differences may be near-zero, but if gender differences are found, it is expected that males will have taken more high school STEM courses than females.

Hypothesis 8: Males will take more high school science and math courses than females.

Prediction of entering or remaining in a STEM field. Various researchers have found that the number of high school math and science courses completed predicts selecting a STEM major by the first or second year of college (Huang et al., 2000; Maple & Stage, 1991; Strenta et al., 1994; Ware & Lee, 1988) and completing a degree in a STEM field (Federman, 2007; Maltese & Tai, 2011). Additionally, in several nationally representative samples of college students, Chen and Weko (2009) found that students taking advanced high school math courses (e.g., trigonometry, pre-calculus, calculus) were more likely to enter STEM fields at some point during college than those who took only lower level math courses in high school (e.g., algebra).

In samples comprised of students majoring in STEM, inadequate high school preparation in advanced math and science has been found to be related to leaving STEM fields (Astin & Astin, 1992; Farmer et al., 1995). For instance, in samples of 9th and 12th grade females expressing interest in pursuing a STEM career, Farmer et al. (1995) found that taking elective science courses in high school was a strong predictor of remaining in a STEM profession ten years later. Chen and Weko (2009) reported that in a sample of first year college students intending to major in STEM, those who had taken trigonometry and pre-calculus during high school were more than twice as likely as those who had completed only algebra to earn a STEM degree six years later; those who had taken calculus in high school were nearly three times as likely as the algebra-only group to complete a STEM degree six years later. However, others have found only small effects of high school science and math course taking on persistence in STEM (e.g., Nauta & Epperson, 2003), which may be due to reduced variability in course taking (e.g., in samples of students interested in STEM, most students take science and math courses throughout high school). Nevertheless, the majority of prior research indicates that high school course taking in STEM should be a predictor of persistence in STEM majors.

Taking courses in math and science during high school likely reflects various factors, including ability (e.g., students who find they are good at math continue to take math courses), interest (e.g., students who intend to pursue a math- or science-oriented career prepare themselves by taking math and science courses during high school), and self-efficacy (e.g., students who believe they are good at math continue to take math courses). Because STEM fields typically require much prerequisite coursework, particularly in math, those who have not invested in the appropriate courses in high school may not be prepared to begin taking courses in a STEM major, increasing the amount of time required to complete degree requirements. Seymour (1995) found that the unexpected length of time required to complete a STEM major was a factor in undergraduates' decisions to leave STEM majors, and a lack of high school preparation can exacerbate the length of time it takes to earn a STEM degree. The long sequence of courses that must be taken in order to successfully earn a STEM degree have led some to identify particular high school math courses as "critical filters" that limit students' options of majors in college (e.g., Sherman, 1982). Unlike other majors, STEM majors typically require academic preparation that must begin during the early high school years. A National Academy of Sciences (2007) committee report noted:

> Students who choose not to or are unable to finish algebra 1 before 9th-grade—which is needed for them to proceed in high school to geometry, algebra 2, trigonometry, and precalculus—effectively shut themselves out of careers in the sciences. In contrast, the decision to pursue a career in law or business typically can wait until the junior or senior year of college. (p. 102)

Because of the important role it plays in preparing students for college STEM majors, high school course taking is expected to predict STEM persistence in both bivariate and multivariate analyses.

Hypothesis 9: High school preparation in math and science will be positively related to persistence in STEM majors.

Self-rated Ability

Gender differences. Self-efficacy, or an individual's "judgment that he or she has the capability to perform a task" (Colbeck, Cabrera, & Terenzini, 2001, p. 175), has been a topic of interest for many researchers concerned about the STEM pipeline, with gender differences being proposed as an explanation for why women are more likely than men to leave STEM fields. In its annual survey of American college freshman, the Cooperative Institutional Research Program reported that when asked to rate their math ability compared to others their age, 54 percent of men and only 36 percent of women believed they were above average (Pryor et al., 2009). Even when rating their overall academic ability, men were more likely to believe they were above average, with 73 percent of men and 66 percent of women indicating they were above average compared to their peers. Using a large, nationally representative sample, Huang et al. (2000) found that high school females reported lower levels of self-confidence in their math ability than did males, even though females reported receiving higher math grades than males. Similarly, Nagy et al. (2008) found that high school females scored higher than males on math achievement tests but still had lower math self-efficacy than males; when controlling for math achievement, significant gender differences in math self-efficacy remained. Males also have higher expectancies for future success in math than females, even when ability tests do not indicate gender differences (Eccles, 1982). These gender differences remain in high-ability samples. In a national sample of students who were entering college, Astin and Astin (1992) found that among the group of students who scored at or above the 90th percentile on the SAT-Math, 64 percent of men and 48 percent of women believed they were in the highest 10 percent in math ability. Four years later, in this same group of high-ability students, 54 percent of men and only 33 percent of women believed they were in the highest 10 percent in math ability. Others have also found that the gender gap in self-rated math ability widens during college. For instance, in a large longitudinal study, Sax (2008) reported that although both men and women experienced a decrease in self-rated math ability during college, the decrease was greater for women; as college freshmen, 44 percent of women and 55 percent of men reported they were above average in math ability, compared to 37 percent of women and 51 percent of men four years later.

These gender differences tend to hold in samples of students intending to pursue careers in STEM fields. Various studies have indicated that in samples of students who were intending to major in, were currently majoring in, or had already received a degree in a STEM field, females had lower math self-efficacy, academic self-confidence, computing skill confidence, and major-specific skill confidence than males (Farmer, Wardrop, & Rotella, 1999; Felder et al., 1995; Vogt et al., 2007). In a sample of students at four selective colleges majoring in STEM fields, Strenta et al. (1994) found that females were more likely than males to question their ability to handle coursework in their major; even after controlling for grades earned in their college STEM courses, females were still more likely than males to doubt their abilities. Similarly, in a sample of undergraduate engineering majors, Colbeck et al. (2001) found that female students were less likely than male students to feel confident in their ability to become engineers; this relationship remained significant even when controlling for ability and educational goals. It is expected that in the present samples, females will have lower self-rated ability in math and science than males.

Some have attributed gender differences in self-rated ability to the different appraisal pattern tendencies of males and females. For example, females may feel they need to work harder than men to achieve high math and science grades, leading them to attribute their good grades to hard work rather than to ability (see Deboer, 1986). In a single-institution sample of chemical engineers, Felder et al. (1995) found that even though men and women had similar SAT-Math scores and similar grades in college math and science courses, women reported feeling less prepared for their introductory engineering courses than did men. Women also rated their engineering-related abilities, computing abilities, and creative problem solving abilities lower than did men. When making self-evaluations of their STEM-related abilities, females seem to be more likely than males to ignore external evidence of their abilities (e.g., high test scores or grades).

Others suggest that females' self-confidence and self-rated ability in math and science domains are influenced by cultural messages that indicate women are not good at math and science (e.g., Astin & Sax, 1996). Math is seen as a stereotypically male domain, and males are expected to be better at math than females, which may lead to lowered expectations and less positive feedback from females' teachers, parents, and peers and to lower math self-confidence among females (see Correll, 2001). Even when male and female performance is at the same level, others may judge males with more lenient standards when the task or domain is traditionally masculine or male-dominated (Koch, D'Mello, & Sackett, 2010), so higher external evaluations may create higher self-evaluations. Eccles (1994) found that parents who endorsed traditional gender role stereotypes tended to overestimate their sons' abilities in traditionally male domains such as physics and to underestimate their daughters' abilities in these fields. Males may receive more positive feedback and encouragement in math or science domains than females who exhibit similar ability and performance, contributing to gender differences in self-rated math and science ability. Males do not tend to overestimate their ability in the traditionally feminine domain of verbal ability (Correll, 2001), leading some to point to the effects of gender stereotypes on self-evaluations.

The previous explanations are related to Bandura's (1982) work indicating that self-efficacy is derived from four types of experiences: performance accomplishments (e.g., prior successes or failures in the domain), vicarious experiences (e.g., observing similar individuals succeed or fail in the domain), physiological states (e.g., high anxiety that leads to self-doubts), and verbal persuasion (e.g., encouragement from others). In turn, self-efficacy influences the three components of motivation: whether to initiate effort, how much effort to expend, and how long to expend effort. If women have more negative STEM-related experiences in these four domains (e.g., women score lower on math ability tests, have fewer successful role models in STEM fields, experience more anxiety, and receive less encouragement than males), this may be a partial cause for their departure from the STEM pipeline. As Bandura (1982) noted, "When beset with difficulties people who entertain serious doubts about their capabilities slacken their efforts or give up altogether, whereas those who have a strong sense of efficacy exert greater effort to master the challenges" (p. 123). Thus, women may be more likely to leave STEM fields not simply because they have, on average, acquired lower levels of STEM relevant skills, but also because they lack confidence in their ability to succeed.

Additionally, because low self-ratings of math ability predict lower enrollment in subsequent advanced math courses in high school, even when controlling for prior math achievement (Nagy et al., 2008), low self-rated ability may also contribute to reduced STEM participation for women through its effects on course taking.

Women's lower self-rated ability may contribute to the gender differences reported for course grades, with women tending to earn higher grades than men. In a survey of more than 200,000 full-time, first-year undergraduates at nearly 300 universities throughout the U.S., the Cooperative Institutional Research Program reported that women were more likely to indicate they expected to need special tutoring or remediation in math (29 percent of women compared to 19 percent of men) and science (15 percent of women compared to 9 percent of men; Pryor et al., 2009). This likely reflects ability and self-rated ability (i.e., women tend to have lower standardized test scores in and to be less prepared in math and science than men, and they have lower confidence in their abilities) as well as contributes to gender differences in grades (i.e., women are more likely to seek special help, which may lead to higher math and science grades than men). Although women may be more inclined than men to leave STEM majors (perhaps partially due to lack of self-efficacy), women who remain may work harder due to this low self-rated ability. Conversely, men, with more confidence in their math and science abilities, may invest less time in coursework. As Bandura (1982) stated, "those who perceive themselves to be supremely self-efficacious in the undertaking feel little need to invest much preparatory effort in it" (p. 123).

Hypothesis 10: Males will have higher self-rated ability in STEM than females.

Prediction of entering or remaining in a STEM field. Results from several studies indicate that self-rated ability in math and science are significant predictors of selecting and persisting in a STEM major (Astin & Astin, 1992; Brainard & Carlin, 1998; Correll, 2001; Deboer, 1986). One's initial reaction to this finding may be that this effect is explained by actual ability; that is, self-rated ability predicts persistence in STEM because it is related to measured ability, which predicts persistence in STEM. However, even when controlling for relevant predictors of self-rated ability (e.g., measured ability), self-rated ability in math and science have been found to remain significant predictors of STEM persistence (e.g., Astin & Astin, 1992; Deboer, 1986). For example, in a longitudinal study of college-bound high school students, Correll (2001) found that self-rated math ability in high school predicted the choice of a quantitative college major during the second year of college; even when accounting for high school grades, test scores, and course taking, the effect of self-rated ability remained a significant predictor of quantitative major choice. Additionally, although one might expect self-rated ability in a domain to be highly correlated with measured ability in that domain, meta-analytic evidence indicates the mean correlation is medium in size (.29; Mabe & West, 1982). However, Mabe and West's (1982) credibility intervals were quite wide, indicating the presence of moderators, one of which was the domain of the self-rating. For the domain most relevant to the present study, scholastic self-ratings, the mean correlation between self-ratings and performance was .42; the mean correlation was also higher when self-ratings were relative and made in comparison to others, which is a feature of the measure used in the present study. Thus, it seems likely that some of the effect of self-rated ability on persistence is driven by actual ability but that a substantial portion is not.

Self-rated ability is related to other predictors of persistence in STEM, such as interest, course taking, and effort exerted in courses (Bandura, 1982; Nagy et al., 2008). That is, those who believe they have high ability in math or science tend to indicate more interest and take more courses in these domains than those who believe they have low ability. Self-rated ability also affects one's expectations for success (see Deboer, 1986), and if people do not believe they will be successful in a domain, it seems unlikely that they will choose to pursue a career in that domain. People who believe they have high ability in a domain are more likely to remain optimistic about future performance and to persist in that domain. Because it has been found to have effects independent of measured ability, self-rated ability is expected to predict STEM persistence in both bivariate and multivariate analyses.

Hypothesis 11: Self-rated ability in STEM will be positively related to persistence in STEM majors.

Interest

Gender differences. Another stream of research focuses on how women's interests and the value they place on math and science may contribute to their underrepresentation in STEM fields. On measures of Holland's (1997) RIASEC model (Realistic, Investigative, Artistic, Social, Enterprising, and Conventional vocational types), more women than men score high on the Social scale, indicating a preference for working with people, for example, to teach, develop, or heal (Lippa, 1998). On the other hand, more men than women score high on the Realistic scale, indicating a preference for manipulating tools or objects (Lippa, 1998). From a young age, females are more likely than males to be interested in working with people, whereas males are more likely than females to be interested in working with things (see Lubinski & Benbow, 2007; Lips, 1992; Su, Rounds, & Armstrong, 2009). Consistent with these findings, Pryor et al. (2009) found that 76 percent of freshman undergraduate women, compared to 61 percent of men considered it essential or very important to help others in difficulty; more men than women (24 percent versus 19 percent) considered it essential or very important for them to make a theoretical contribution to science. In a national sample of college graduates, Daymont and Andrisani (1984) found that women were more likely than men to prefer helping others and working with people in their careers, whereas men were more likely than women to place a high importance on choosing a career that would allow them to make a lot of money and be a leader. Furthermore, these preferences explained some of the variance in career choices; those who preferred working with people were less likely to choose STEM majors.

In addition to gender differences in these broader preferences, gender differences in more specific math- and science-related preferences emerge quite early. In middle and high school, females are less likely than males to participate in math- or science-related extracurricular activities, to be interested in taking or to enjoy classes in math or science, to have positive attitudes toward math, to feel that math will be useful in their future, or to want to pursue a career in math or science (Catsambis, 1994; Eccles, 1982; Huang et al. 2000; Maple & Stage, 1991). In a meta-analysis, Weinburgh (1995) found that, on average, boys had slightly more positive attitudes toward science than did girls; however, in samples of high performing students, no gender differences were found. In a national sample of eighth graders, Huang et al. (2000) found that nearly 8 percent of females wanted to pursue a technical, science, or engineering career, compared to 17 percent of males. Similarly, among entering college freshman, women are less likely than men to intend to major in most STEM fields. Sax (2008) reported the largest difference for engineering, with 14.5 percent of freshmen men and only 2.5 percent of freshmen women planning to major in engineering. Meta-analytic evidence confirms that males indicate higher interest in science, math, and engineering than do females, and these gender differences have tended to remain quite constant over the past several decades (Su et al., 2009). Within STEM fields, one exception to this pattern may be the biological sciences. For instance, Miller, Blessing, and Schwartz (2006) found that whereas female high school students enjoyed most math and science courses less than males, females enjoyed biology more than males did. Sax (2008) reported that among entering college freshmen, 9.2 percent of females and 7.4 percent of males intended to major in biological sciences. To summarize, in national samples, males tend to show more interest in STEM (e.g., via reports of enjoyment, interest, positive attitudes, or intended careers), but a different pattern tends to be found for the biological sciences, with females showing more interest than males.

Some have found that even in samples of students who have high math or science ability, males are more likely than females to pursue careers in most STEM fields. For instance, in the Study of Mathematically Precocious Youth (SMPY, Benbow, Lubinski, Shea, & Eftekhari-Sanjani, 2000; Benbow & Stanley, 1982; Lubinski & Benbow, 2007), a group of 12- to 14-year-olds identified as mathematically gifted (i.e., scoring in the top 1% for their age group) was followed longitudinally. In the group of nearly 2,000 participants who reported educational and career outcomes 20 years later, educational attainment was high above the national base rate (e.g., over 90 percent of participants received bachelor's degrees, compared to 23 percent of the American population at that time). However, males were more likely than females to earn degrees (both bachelor's and graduate) in computer science, engineering, and physical science, whereas females were more likely than males to earn degrees in the biological science and in health fields. Males and females were equally satisfied with their careers, but males were more than twice as likely as females to be employed as math or computer scientists and engineers. To further explore why highly talented women were less likely than men to pursue careers in most STEM fields, Benbow et al. (2000) asked participants about their values and life priorities, finding that men placed more importance on achieving work success, having a fulltime career, creating something that would have an impact, and making a lot of money than did women. On the other hand, women placed more importance on maintaining strong relationships with friends and family and on having children. In another subsample of SMPY, Lubinski and Benbow (1992) reported that males had stronger theoretical values, which are characteristic of physical scientists, and females had stronger social values, which are negatively correlated with interest in physical sciences. These studies identify gender differences in values and priorities that may help to partially explain why talented women are more likely than men to choose non-STEM careers, given the requirements of many STEM professions. Lubinski and Benbow (1992) concluded that "males, compared with females, tend to have ability and preference profiles more congruent with optimal adjustment in math and science careers. As a result, one would expect more males than females in such careers" (p. 64).

Gender differences in interest have been found to hold up in samples of students intending to pursue STEM careers. For example, in a sample of high achieving high school students with strong interests in STEM, Lee (2002) found that STEM was more central to males' than to females' identities, with STEM activities being more important to males. Similarly, Ware and Lee (1988) found that male STEM majors had more positive attitudes toward math than did female STEM majors. In a single-institution sample of entering college freshmen who indicated an interest in majoring in a STEM field, Ware et al. (1985) found that men were more likely than women to report that a science course was the most enjoyable course of their first year of college. Even in samples of students interested in STEM, males tend to show stronger interest than females.

Those studying persistence in STEM have also identified interest as an important factor that may contribute to gender differences. For instance, in a large-sample study on persistence in science during college, Astin and Sax (1996) found that women who left science between their first and fourth years of college were more likely than men to leave because of a service orientation or a desire to help others. If women do not see STEM fields as helping professions, they may be less interested in remaining in STEM majors. In a longitudinal study of computer science majors at a selective university, Margolis et al. (2000) found that many females felt that they were not as interested in the content as were their male classmates, which led to doubts about whether they had chosen the right major, and in some cases, transferring out of the major. In a multiple-college study on leaving STEM majors, Seymour (1995) found that more women than men left STEM majors because another major offered greater intrinsic interest. Therefore, women may leave STEM fields at higher rates than men because they lose interest or because other fields appear more interesting (Brainard & Carlin, 1998). In the present study's samples of students interested in STEM majors, it is expected that males will indicate more interest in STEM (operationalized as participation in extracurricular STEM activities or earning awards in STEM fields and as high school intentions to major in STEM fields) than females.

Many have pointed to the role of gender stereotypes as a potential cause of gender differences in preferences for a STEM major or career, as science and math continue to be viewed as masculine professions (see Nassar-McMillan, Wyer, Oliver-Hoyo, & Schneider, 2011). For instance, using an implicit association test[1] to examine attitudes toward math and science relative to language and arts, Nosek, Banaji, and Greenwald

[1] Implicit association tests use participants' response speeds to different pairings of stimuli to infer their automatic associations. During the test, when a word appears on the computer screen, participants must quickly press one of two keyboard keys that correspond to the word. For example, to examine participants' associations between science and gender and between liberal arts and gender, one block of trials would require participants to press one key if the word that appeared was related to science or males and to press another key if the word that appeared was related to liberal arts or females. In another block of trials, these pairings would be switched, and participants would press one key if the word that appeared was related to liberal arts or males and press another key if the word was related to science or females. If a participant responded more quickly when males were paired with science and females were paired with liberal arts on the keyboard than when males were paired with liberal arts and females were paired with science on the keyboard, the participant would be said to have an automatic association between males and science (relative to the other possible pairings). The strength of this automatic association is based on the magnitude of differences in response speeds for the different pairings. See Greenwald, Nosek, and Banaji (2003) for additional details and examples.

(2002) found that both males and females had implicit beliefs that math is a male rather than female field. Women with stronger stereotypes about math being a male field also had less liking for math, lower personal identification with math, and performed worse on the SAT-Math. The opposite pattern of relationships was found for men; the stronger the belief that math is a male field, the more positive the math attitudes, the stronger the math identity, and the higher the SAT-Math score. Gender stereotypes of occupations may contribute to females' interests by leading to reduced support, encouragement, and expectations and by discouraging them from considering male-dominated fields. For example, in a study using a national sample of high school girls who were academically prepared for college STEM courses, the Extraordinary Women Engineers project (2005) found that many girls considered engineering to be a "man's job" that girls are not interested in. Some girls also noted that they were not exposed to engineering or encouraged to pursue it. Additionally, many undergraduates majoring in engineering believed that most young women are not aware of what engineers actually do and do not realize that it may be interesting and relevant to their goals. Even in a group of females who were majoring in a STEM field, Wasburn and Miller (2004) reported that 30 percent were uncertain or did not believe that technology careers were appropriate for women. If women do not believe math and science are valuable or appropriate for them, it is reasonable that they are not as interested as males in taking math or science courses or pursing a major requiring extensive math or science coursework.

The anticipated workplace environment in STEM professions may also reduce women's interest in STEM. If females view STEM fields as masculine, they may anticipate discrimination or disapproval during their educational and occupational careers, making the fields less attractive than fields that are seen as less masculine or male-dominated. Additionally, “women tend not to identify with traditional notions of what it means to have a career in STEM and may therefore choose not to pursue majors or careers in STEM” (Shaprio & Sax, 2011, p. 12). That is, stereotypes portraying scientists and mathematicians as loners who work long hours and have little time for their families (see Eccles, 1994) may deter more females than males from pursuing these careers. Consistent with traditional gender stereotypes, females have been found to place higher value on their family role than on their career role whereas males place equal value on family and career roles, and women are more likely than men to say they will make career sacrifices for the sake of their family (Eccles, 1994). Women’s tendency to prioritize their family over their career may make STEM careers, which are seen as requiring long hours and extensive time away from family, less appealing to women than to men. Beliefs about STEM careers and about the environments in which STEM professionals work may lead to the loss of more females than males from the STEM pipeline.

Hypothesis 12: Males will indicate higher interest in STEM than females.

Hypothesis 13: Males will have higher participation in extracurricular STEM activities, earn more STEM awards, and hold more STEM officer positions than females.

Prediction of entering or remaining in a STEM field. Positive attitudes toward and interest in math during middle and high school predict entry into a STEM major during college (Lapan, Shaughnessy, & Boggs, 1996; Ware & Lee, 1988). For instance, Tai et al. (2006) found that eighth grade students who stated that they planned to have a science career were 1.9 times more likely than those planning to have a non-science career to earn a bachelor's degree in a life science field. Students who wanted to be scientists were 3.4 times more likely than those who did not want to be scientists to earn a degree in physical sciences or engineering. Similarly, Maltese and Tai (2011) found that seniors in high school who planned to earn a degree in STEM were more than three times as likely to earn a STEM degree as students who planned to earn a non-STEM degree. Even after controlling for relevant ability and background variables, interest tends to remain a significant predictor of selecting a STEM major (e.g., Maltese & Tai, 2011; Strenta et al., 1994).

The use of interest to predict persistence among those who intend to earn STEM degrees is less common, but a few researchers have found that strength of interest is a significant predictor of continuing in STEM. For instance, in a sample of high school girls who attended a conference for students interested in STEM careers, Nauta and Epperson (2003) found that the higher the scores on Technical and Science dimensions of an ACT interest inventory (which correspond to Holland's [1997] Realistic and Investigative themes, respectively), the more likely the student was to choose a STEM major in college. Similarly, in a single-institution longitudinal study, Stinebrickner and Stinebrickner (2011) found that in a sample of freshmen who intended to major in a STEM field, declining interest in STEM throughout the first two years of college was associated with leaving STEM majors for a non-STEM major. In the present study, interest in STEM (represented by participation in extracurricular STEM activities, awards in STEM, and high school intentions to major in STEM fields) is expected to predict persistence in STEM majors. Because some previous evidence indicates that interest predicts persistence even when controlling for other relevant factors, interest in STEM is expected to predict persistence in both bivariate and multivariate analyses.

In addition to the obvious explanation for why interest is related to selection of or persistence in a STEM major (i.e., people continue to do things that they are interested in and quit doing things that do not interest them), interest in STEM is likely both a cause and effect of various predictors that are relevant to persistence in STEM. For example, students who are high achievers in math may be interested in math because they have discovered that they are good at it, and students who are interested in math may become high achievers because their interest motivates them to develop their math skills. Margolis et al. (2000) noted:

> It is hard to disentangle one influence from the other, to know how they interact. Women's interest (or lack thereof) may not be as intrinsic as it feels, for interest is continuously encouraged or extinguished, and defined, by cultural norms, external factors, and internal responses. (p. 116)

This type of reciprocal relationship is likely found between interest and various predictors, such as measured ability and achievement, investment through course taking or extracurricular activities, self-rated ability, and course grades. Nevertheless, interest is expected to be directly related to persistence in STEM fields.

Hypothesis 14: High school interest in STEM will be positively associated with persistence in STEM majors during college.

Hypothesis 15: The quantity of extracurricular activities, awards, and officer positions in STEM will be positively related to persistence in STEM majors.

Ability, Course Grades, and Interest in Non-STEM Domains

Gender differences. Gender gaps for abilities and achievement in domains outside of math and science, particularly in the verbal domain, have been documented, with females scoring higher than males on some tests of verbal ability (particularly speech production, meta-analytic *d*-value of .33; Hyde & Linn, 1988) and writing ability (Mattern & Patterson, 2012). Additionally, as early as middle school, females tend to rate their verbal ability higher than their math ability, to believe that English classes are easier than math classes, and to believe that English is more useful and valuable than math (Eccles, 1982). That is, women may have stronger relative strengths in verbal or other non-STEM domains, compared to men. Women's relative success, interest, and self-efficacy in non-STEM domains may draw them away from math and science. Some research also suggests that women have a wider variety of goals and interests than men, so women may have more interests and options that pull them away from STEM. Eccles (1994) reported that for interest inventories and occupational interests, females were more likely than males to be interested in multiple domains, whereas males tended to rate their interest in one domain as high and in the other domains as low. A wider variety of interests for women may contribute to more major switching during college.

Even in samples of students pursuing STEM majors, females may have higher ability and interest in non-STEM domains than males. For instance, in a sample of students entering four selective colleges and intending to major in STEM fields, Strenta et al. (1994) found that females earned higher non-STEM GPAs during their first two years of college than did males. Among those in this sample who switched to a non-STEM major, females were more likely than males to explain their major switch by noting that other fields made better use of their talents than did STEM fields. Because women are more likely than men to have relatively high interests and talents in fields that are not math- and science-oriented, women may also be more likely than men to pursue these other fields instead of STEM fields. In the current study, relative strength in non-STEM versus STEM domains is measured as tilt, or the difference between non-STEM and STEM ability/achievement. SAT tilt is SAT-Critical Reading minus SAT-Math. Undergraduate GPA tilt is non-STEM GPA minus STEM GPA. For both variables, females are expected to have more positive tilt (i.e., stronger relative non-STEM to STEM ability and achievement) than males.

Hypothesis 16: Females will have a more positive SAT tilt than males.

Hypothesis 17: Females will have a more positive undergraduate GPA tilt than males.

Prediction of entering or remaining in a STEM field. There is some evidence indicating that non-STEM abilities and grades may pull students away from STEM majors. High school reading and verbal ability test scores (e.g., ACT-Verbal, SAT-Verbal) are negatively related to selecting a STEM major in college (Matsunaga, 1997;

Stinebrickner & Stinebrickner, 2011; Strenta et al., 1994). Using the College & Beyond database that contained SAT scores and majors of students who earned degrees at 12 universities at three points in time (cohorts entering college in 1951, 1976, and 1989), Turner and Bowen (1999) found that among students with high SAT-Math scores (750 or higher), students with lower SAT-Verbal scores were more likely than those with higher SAT-Verbal scores to earn engineering degrees. Correll (2001) found that in a sample of high school students, higher grades in English and higher verbal ability test scores were negatively related to self-assessments of math ability; these relationships were significant even when controlling for math grades and test scores, course taking, and demographic variables, leading to the suggestion that students make relative judgments of their domain-specific abilities.

In samples of students who are majoring in STEM, multiple researchers have found that non-STEM abilities and grades influence retention in STEM majors. For instance, in a study with a sample of engineering majors from seven colleges, Colbeck et al. (2001) reported a negative relationship between SAT-Verbal scores and intention to persist in engineering majors; SAT-Verbal scores remained a significant predictor even when controlling for other background and environmental variables. In a single-college study, Ost (2010) examined leaving physical and life science majors from the time of admission to college, when students indicated their intended majors, to the time of graduation from college, finding that as students' non-science grades improved, they became less likely to remain in their intended physical or life science major. Therefore, it is predicted that relative strengths in non-STEM compared to STEM domains will be related to persistence in STEM majors. A more positive SAT tilt (i.e., a higher SAT-Critical Reading relative to SAT-Math score) is expected to be associated with lower persistence in STEM. Similarly, a more positive undergraduate GPA tilt (i.e., higher non-STEM relative to STEM grades) is expected to be negatively related to STEM persistence.

Due to limited time and resources, all students must choose among various options for courses and majors, and ability or interest in non-STEM domains may pull students away from STEM majors. A person's evaluations of interest or ability may be relative, such that even if one has high achievement or ability in STEM domains, he or she may choose to pursue another domain of study in which his/her ability and achievement are even higher. Scores on ability tests may have a larger impact on initial major selection than on major switching during college because they are known at the time of college entry. Non-STEM undergraduate GPA may provide students with information about their relative strengths and weaknesses and is expected to impact persistence in STEM during college.

Hypothesis 18: SAT tilt will be negatively related to persistence in STEM majors.

Hypothesis 19: Undergraduate GPA tilt will be negatively associated with persistence in STEM majors.

Educational Goals

Gender differences. Research on gender differences in degree aspirations has resulted in mixed findings. In nationally representative samples of high school and college students, it is often found that women have slightly higher degree goals than men, but differences are typically small. For instance, Pryor et al. (2009) found that first year college women were more likely than men to plan to earn advanced degrees (i.e., master's degree or higher, 77 percent of women versus 73 percent of men). Similarly, in a national survey of entering college freshmen, Astin (1998) found that slightly more women than men planned to pursue advanced degrees (68% and 65%, respectively). Considering that women are more likely than men to earn bachelor's and master's degrees (National Science Foundation, 2008), it is not surprising that females have higher degree goals than men. However, men are more likely to earn doctoral degrees (National Science Foundation, 2008), and degree aspirations do not appear to be very stable during the high school and college years. Astin and Astin (1992) found a correlation of only .35 between planned degree goal during one's senior year of high school and planned degree goal four years later. Students with better high school GPAs, more biological and physical science courses in high school, higher SAT-Verbal scores, higher academic self-esteem, and better grades in college were more likely to adjust their degree goal upward (i.e., to intend to pursue a more advanced degree than what they had initially intended). In a longitudinal study of university-bound Canadian students, Shapka, Domene, and Keating (2008) also found that degree goals changed over time, with females having higher educational aspirations early in high school and males having higher degree goals at the point of high school graduation and during college.

The sparse evidence on degree goals for students intending to pursue STEM careers indicates that compared to nationally representative samples, the pattern of gender differences may be reversed. For instance, in samples of 9^{th} and 12^{th} graders who intended to pursue STEM careers, Farmer et al. (1995) found that males had higher career aspirations (a variable comprised of the level of education they planned to complete and the prestige of their intended occupation) than did females. Similarly, in a single-institution sample of chemical engineers, Felder et al. (1995) found that during their junior and senior years of college, males were three times as likely as females to intend to go to graduate school. Because the present study uses samples of students who showed prior interest in STEM majors, males are expected to have higher degree goals than females.

Hypothesis 20: Males will have higher degree goals than females.

Prediction of entering or remaining in a STEM field. Using national samples of high school and college students, a few studies have indicated that degree aspirations are related to pursuing a STEM degree. For example, Chen and Weko (2009) found that college students planning to earn a graduate degree in the future were more likely than those aspiring to a lower degree to enter STEM majors. Similarly, in a large sample of high school students, Ware and Lee (1988) found that educational aspirations (represented by college expectations and the highest level of education aspired to) predicted choosing a STEM major over a non-STEM major.

Persistence among those already in the STEM pipeline is also predicted by degree goals. In a sample of first-year college students intending to major in STEM, those intending to earn a graduate degree were more likely than those intending to earn lower degrees to have earned a STEM degree six years later (Chen & Weko, 2009). Similarly, Huang et al. (2000) found that in a sample of college freshmen at four-year universities who had declared a STEM major, those who reported aspirations to attend graduate school were more likely than those who planned to earn only a bachelor's degree to obtain a STEM degree within five years. These findings lead to the prediction that educational goals will predict persistence in STEM majors.

A student's degree goal may serve as an indicator of educational commitment and motivation. Students who intend to earn graduate degrees may be more willing to put forth the effort required to succeed during their undergraduate years, as an undergraduate degree is required to pursue graduate studies. They also may be committed to the idea of attending school for many years before entering the workforce and to persisting through academic challenges. Thus, those who are already in STEM majors may be more likely to persist if their ultimate goal is a graduate degree. As a representation of a goal and commitment, degree aspirations are likely to predict persistence toward the goal (e.g., Locke, Shaw, Saari, & Latham, 1981). However, one may change majors and retain prior degree aspirations; for example, instead of a goal of attending graduate school in a STEM field, the goal may be to attend graduate school in a humanities department. Nevertheless, existing research suggests that degree goals predict persistence in the STEM pipeline.

Hypothesis 21: Degree goal will be positively associated with persistence in STEM majors.

Demographic Correlates

Two common demographic variables are discussed here due to their potential impact on entry into or persistence in a STEM major. Socioeconomic status (SES), or "the social standing or class of an individual or group," often conceptualized as some combination of income, education, or occupation (American Psychological Association, 2013), and race/ethnicity may influence entry or persistence in STEM due to their representation of different cultural values, financial-related concerns, schooling experiences, and family expectations and experiences. Through their relationship with these other, non-measured variables (e.g., cultural and financial factors), demographic variables are expected to affect persistence in STEM majors.

SES. The findings regarding the impact of SES on selection of a STEM major are inconsistent. Although some find that higher SES is positively associated with the selection of a STEM major (e.g., Cole & Espinoza, 2011; Federman, 2007; Huang et al., 2000), others find the opposite (e.g., Astin & Astin, 1992). For example, in a national sample of high school students, Huang et al. (2000) found that students whose parents had completed college were more likely than those whose parents had less education to choose a STEM major during their second year of college. On the other hand, Ma (2009) reported that SES was negatively correlated with majoring in a STEM field, with lower SES students being more likely than higher SES students to choose a major in a STEM field during the early stages of college. Some have found that SES predicts receiving a degree in a STEM (compared to a non-STEM) field and that SES remains a significant predictor when controlling for prior achievement, course taking, and interest in STEM (Federman, 2007). However, others have found that after SES is included in a regression model with other individual-level predictors such as interest, academic performance, self-confidence, and course taking, the effect of SES is not significant (e.g., Huang et al. 2000; Maltese & Tai, 2011; Trusty, 2002).

Although the findings regarding the effect of SES on selection of a STEM major in nationally representative samples are mixed, the effects of SES on persistence among those already in the STEM pipeline are more consistent. SES has been found to be positively associated with persistence in STEM among those who are interested in pursuing STEM careers. For instance, using national statistics for the entering college class of 1995, Baum, Ma, and Payea (2010) reported that among students who chose STEM majors at college entry, approximately half of those whose parents were four-year college graduates completed a STEM credential, whereas approximately one-third of those whose parents had less education completed a STEM credential. Chen and Weko (2009) and Gayles and Ampaw (2011) also reported significant effects of parents' education and income on persistence in STEM majors and attainment of STEM degrees. In a longitudinal study of eighth graders who planned to pursue a STEM career, Mau (2003) found that in a follow-up two years after high school, those who persisted in STEM were from higher SES families than those who had left STEM; however, SES was not a significant predictor of persistence when included in a regression model with academic and self-efficacy predictors. Therefore, persistence in STEM is expected to be predicted by SES, but the effect of SES may disappear when other relevant predictors are considered simultaneously.

Different explanations can be given for why SES may be positively or negatively related to entry into or persistence in a STEM major during college. Some researchers have cited parents' expectations for their children as an important factor. Ware et al. (1985) noted that parents with more education are likely to have less conventional ideas about gender roles and as a result, be more willing to encourage their daughters to pursue careers in male-dominated domains such as most STEM fields. Low SES students also may be less likely to have personal role models who work in STEM fields, so they may be less likely to consider STEM careers or to believe they can be successful in a STEM occupation. Whereas some of the barriers created by coming from a low SES background may be reflected in commonly-studied predictors of majoring in STEM (e.g., ability test scores, grades), others may be more difficult to quantify. For example, students from different SES backgrounds may have high school transcripts that look similar (e.g., comparable course titles and grades in STEM), but if low SES students are more likely than high SES students to attend low-quality high schools, they may be less prepared for college-level STEM coursework due to the quality of their prior educational. Thus, students who appear quite similar at college entry may have different levels of performance and rates of persistence in STEM during college.

Low SES also may increase barriers to STEM entry through financial difficulties and family situations. For example, low SES may be associated with fewer STEM enrichment opportunities, more educational disruption, or lower quality educational environments (e.g., attending low-quality schools), leading to poorer preparation for STEM careers and perhaps to reduced interest in STEM. Financial concerns of lower SES students during college may lead to reduced persistence. For example, due to the hierarchical sequencing of courses in typical STEM majors, students can likely find non-STEM majors that could be completed much more quickly than STEM majors, reducing the amount of time and money spent on college.

On the other hand, some researchers point to financial concerns of students from lower SES backgrounds as making them more likely to enter and persist in STEM fields. Whereas higher SES students may not worry about choosing a major where expected earnings are relatively low, lower SES students may be more likely to focus on expected earnings. Financial concerns may be more salient for lower SES students, and they may be more motivated to enter STEM professions if they view them as occupations in which earnings will be high (e.g., if they believe that “engineering is where the money is”, Tharp, 2002, p. 105). That is, if STEM majors are viewed as leading to high paying jobs, they may be more attractive to lower SES students due to the presence of financial concerns.

Hypothesis 22: SES will be positively related to persistence in STEM majors.

Race/ethnicity. The patterns for STEM entry by race/ethnicity are well-documented, with college-going Asian students being more likely than undergraduates of any other race/ethnicity to select STEM majors and to earn degrees in STEM fields. Among all Asian students who earned bachelor’s degrees in the U.S. in 2009, 23 percent earned STEM degrees, compared to 14 percent of White, 12 percent of Hispanic, and 11 percent of Black students (President’s Council of Advisors on Science and Technology, 2012). Some report that even after controlling for other predictors such as high school course taking, achievement, and interest, race remains a significant predictor of earning a STEM degree (e.g., Federman, 2007), but some find that race is not significant when other predictors are accounted for (e.g., Maltese & Tai, 2011).

STEM persistence rates for racial/ethnic groups are often similar for national college samples and samples of STEM majors. Asian students tend to show higher persistence rates than any other race/ethnicity, and White students tend to show higher persistence than Black, Hispanic, and American Indian students (e.g., Astin & Astin, 1992; Chen & Weko, 2009; Huang et al. 2000; Smyth & McArdle, 2004). Using national statistics for the entering college class of 1995, Baum et al. (2010) reported that of those who chose STEM majors at college entry, only 16 percent of Hispanic and Black students earned bachelor's degrees in a STEM field, compared to 30 percent of Asian and White students. Similarly, in a multi-college study, Bonous-Hammarth (2000) found that 44 percent of disadvantaged ethnic minorities left STEM majors from the first year of college to the fourth year of college, whereas approximately 25 percent of White and Asian American students left STEM majors during this time period. In the prediction of persistence, many report that even after controlling for other relevant predictors such as ability, achievement, and self-efficacy, race is a significant predictor of persistence (e.g., Smyth & McArdle, 2004; Mau, 2003; Ost, 2010). Racial or ethnic differences in STEM entry or persistence may be partially driven by racial or ethnic differences in educational beliefs and values, schooling experiences and quality, and family experiences that contribute to interest, investment, and achievement in STEM fields (see Barton, 2003; St. John, Hu, Simmons, Carter, & Weber, 2004).

> *Hypothesis 23*: Asian students will be more likely than those in any other racial/ethnic group to persist in STEM majors, and White students will have higher persistence rates than Black and Hispanic students.

Summary of Individual-level Predictors

To summarize, individual-level predictors that are hypothesized to be positively associated with persistence in STEM majors are SAT-Math, high school achievement, undergraduate STEM grades, high school course taking in STEM, self-rated STEM ability, high school extracurricular activities and awards in STEM, high school interest in STEM, degree goal, and SES. SAT tilt and undergraduate GPA tilt are expected to be negatively associated with STEM persistence. Racial differences are hypothesized, with Asian students being expected to have the highest persistence rates, followed by White and then by Black and Hispanic students. Males are predicted to have higher persistence rates than females. The direction of all of these relationships is expected to remain the same for bivariate and multivariate analyses.

Gender differences are hypothesized for many predictors, with males being expected to score higher than females on SAT-Math, high school STEM course taking, self-rated STEM ability, extracurricular activities and awards in STEM, high school interest in STEM, and degree goal. Females are expected to outperform males on high school achievement and to have a more positive SAT tilt and undergraduate GPA tilt. Additionally, college STEM GPA is hypothesized to interact with gender, with females expected to be more likely than males to leave STEM after earning poor STEM grades. No hypotheses are offered for gender differences for college STEM grades, SES, or race/ethnicity.

School-level Predictors

Several college-level variables have been proposed as being relevant to students' entry into and persistence in STEM majors. Females' proportional representation in STEM at a college may be associated with STEM entry and retention for females due to the added pressures of being underrepresented. College selectivity (typically operationalized as a college's admission rate or the entrance exam scores of entering students) may affect STEM entry and retention through its relationship with course difficulty and peer characteristics. Finally, whether a school is public or private may affect STEM persistence through its association with the quality of instruction.

Female representation in STEM. A few researchers with multi-college samples have explored the impact of women's proportional representation in their college major departments on persistence. For instance, in a study on retention among undergraduate computer science majors at colleges in Virginia, Cohoon (2001) found that gender differences in retention rates varied across colleges; females at some colleges left computer science at much higher rates than males, but females and males at other colleges had similar retention rates. One factor associated with equal retention rates for males and females was the presence of at least one female faculty member. Another factor was the presence of a sufficient number of female students in major courses. The higher the proportion of female undergraduates in the computer science department, the higher the female retention rates at that school. Similarly, it has been found that both the proportion of female undergraduates and the proportion of female faculty in a department predict persistence in traditionally male majors (see Sax, 2008). Therefore, it is expected that undergraduate females' representation in STEM at a college will predict their persistence in STEM.

Kanter's (1977) classic work on proportional representation provides an explanation for why the proportion of women in a group may lead to decreased performance and persistence among women. When women are few in number in a setting, they become tokens or "stand-ins for all women" who are seen as "representatives of their category, as symbols rather than individuals" (Kanter, 1977, p. 382). Because others are more prone to make stereotyped judgments about women when women are rare in the group, women may face more discrimination as the environment becomes more male-dominated. Kulis, Sicotte, and Collins (2002) noted that "failure to achieve a 'critical mass' of women in the field…fuels stereotyping of female colleagues, stifles the development of women's professional networks, and impedes institutional change, thereby compromising women's chances of unbiased evaluations" (p. 661). Women may be constrained in their behaviors because they are expected to behave in stereotypical ways, which may lead to stress and dissatisfaction. Token women may experience "the loneliness of the outsider, of the stranger who intrudes upon an alien culture" (Kanter, 1977, p. 382). However, as more similar members join the group, the potential for forming alliances and for influencing the culture of the group increases, leading to a more welcoming environment for women.

Females in STEM fields may benefit from same-sex classmates and mentors (see Astin & Sax, 1996), and at schools where more females choose STEM majors, females are more likely to see students like them succeed in STEM, to have female classmates who provide support, and to have same-sex mentors. Additionally, as women lose their token status, others may begin to see them as individuals rather than as representatives of their group, likely leading to reduced discrimination and perhaps to more equal expectations for men and women. Women are less likely to choose majors that are male-dominated (e.g., most STEM fields) than those that are not male-dominated, and their proportional representation may be associated with the levels of constraints, pressures, and discrimination they face, which may affect their performance and persistence in STEM majors (Kanter, 1977). Even though STEM occupations, overall, are male-dominated (President's Council of Advisors on Science and Technology, 2012), women's representation at a particular college may influence persistence of women at that college. As Kanter (1977) noted, "People's treatment, then, is not automatically fixed by inflexible characteristics but depends on their numbers in a particular situation. Change in the behavior and treatment of women in token positions is strongly tied to shifting proportions" (p. 395).

Hypothesis 24: The school-level proportion of undergraduate STEM students who are female will predict persistence in STEM majors for females; persistence of females will increase as their proportional representation in STEM increases.

College selectivity. Although overall persistence rates (i.e., graduation rates) have been found to be higher at more selective compared to less selective universities (see Smyth & McArdle, 2004), it is not clear whether persistence in STEM will be associated with institutional selectivity. Chen and Weko (2009) found that the more selective the institution (based on the SAT scores of entering freshmen), the greater the retention in

STEM fields; among students who entered college with the intention of earning a STEM degree, more than twice as many students at very selective schools than at less selective schools had earned a bachelor's degree in STEM six years later. On the other hand, Astin and Astin (1992) found that students were more likely to leave physical science majors between their first and fourth years of college at more selective institutions than at less selective institutions. Others have found that after controlling for students' characteristics, college selectivity is not a significant predictor of persistence in STEM (e.g., Smyth & McArdle, 2004). Due to these conflicting findings, no hypothesis is offered in the present study for the effects of institutional selectivity (represented by a college's undergraduate admission rate and by SAT scores of entering undergraduate students) on persistence in STEM.

Competing rationalizations can be provided to explain this inconsistent pattern of findings. Students entering selective colleges tend to be academically prepared and have high ability, so they may be better equipped to succeed in STEM majors than students attending less selective colleges. On the other hand, courses may be more difficult at selective universities than at less selective universities (e.g., due to curved grading, adjustment of course difficulty based on student ability). Furthermore, students at more selective universities have more academically able peers, which may affect their self-evaluations and lead them to question their ability to succeed in the major. That is, comparing oneself to one's peers may lead to changes in self-assessments such that students do not only make absolute judgments of their abilities but also make self-assessments based on the abilities of other students with the same major. When students are surrounded by other high ability students, their self-rated ability may decrease, potentially leading to decreased STEM persistence. Students who are in the top third of their college's SAT-Math score band are nearly twice as likely as those in the middle third and over three times as likely as those in the bottom third to earn a STEM degree at that college (see Smyth & McArdle, 2004). Thus, holding SAT-Math constant, a student may be more likely to earn a STEM degree at a less selective university than at a university where he/she will have low ability compared to peers. Existing research does not clearly indicate which of these explanations is most plausible.

Public/Private. Some have examined the impact of attending public versus private colleges on persistence in STEM. For instance, in a sample of nearly 30,000 entering students at 388 colleges, Astin and Astin (1992) found that attending a public university was significantly negatively associated with earning a degree in STEM, even after controlling for a variety of relevant individual- and school-level predictors. Similarly, Huang et al. (2000) reported that in a sample of college freshmen majoring in STEM, students attending private colleges were more likely than those attending public colleges to persist and earn degrees in STEM fields; this effect remained significant even after accounting for background and attitudinal variables. Those offering explanations for this effect typically focus on differences in instruction at public and private colleges. Public schools often have larger classes, make more use of graduate student instructors, and have faculty who are more focused on research than on teaching. These qualities can lead to reduced opportunities for students attending public schools (compared to those at private schools) to have meaningful interactions with faculty and may "create an environment that serves to alienate university students and to discourage them from the study of science" (Astin & Astin, 1992, p. 6).

Hypothesis 25: Persistence in STEM majors will be higher at private universities than at public universities.

Summary of Hypotheses, Research Questions and Contributions of Study

In the present study, I examine the following individual-level variables as potential predictors of STEM persistence and as potential explanations for gender differences in persistence: SAT-Math, SAT tilt (i.e., SAT-Critical Reading minus SAT-Math), high school achievement (comprised of cumulative high school GPA, high school STEM GPA, and class rank), high school STEM coursework (comprised of the number of STEM courses and STEM honors courses taken in high school), self-rated ability in STEM, high school interest in STEM, high school extracurricular activities and awards in STEM, degree goal, race/ethnicity, SES, college STEM achievement (i.e., undergraduate STEM GPA), and undergraduate GPA tilt (i.e., non-STEM GPA minus STEM GPA). The school-level variables studied are public/private, college undergraduate admission rate, SAT scores of entering undergraduate students, and proportion of undergraduate STEM majors who are female. In samples of students indicating interest in STEM majors, I examine differences between men and women and between students who persist in STEM majors and those who leave STEM majors, as well as identify factors that independently contribute to the choice to persist in a STEM field.

Gender differences. Based on the research discussed in the previous sections, it is hypothesized that males will have higher values than females for the following variables: SAT-Math, high school STEM coursework, self-rated ability in STEM, high school interest in STEM, high school extracurricular activities and awards in STEM, and degree goal. Females are expected to have higher values than males for high school achievement, SAT tilt, and undergraduate GPA tilt. Because previous research on gender differences is inconsistent or lacking for some predictors, no hypotheses regarding gender differences are offered for college STEM grades, SES, or race/ethnicity.

Individual-level predictors. It is expected that those who persist in STEM majors will have higher values than those who leave STEM majors for the following variables: SAT-Math, high school achievement, college STEM grades, high school STEM course taking, self-rated ability in STEM, high school interest in STEM, high school extracurricular activities and awards in STEM, degree goal, and SES. Those who persist in STEM are expected to have lower values than those who leave for SAT tilt and undergraduate GPA tilt, as relatively higher ability or achievement in non-STEM domains may pull students away from STEM. Asian students are expected to have the highest persistence rates of any race/ethnicity, followed by White students, and then by Black and Hispanic students. Males are expected to have higher persistence rates than females. An interaction between college STEM grades and gender is expected, with poor STEM grades expected to have a larger effect on persistence for females than for males.

School-level predictors. It is expected that for females, the proportion of STEM undergraduates who are female will predict persistence such that the larger the proportion of undergraduate females in STEM departments at a college, the greater the persistence among female STEM majors at that college. That is, the proportion of females in STEM is expected to be a predictor of persistence only for female students (i.e., a cross-level interaction between the proportion of females in STEM at a college and the gender of the individual student). Because proportional representation is hypothesized to be a factor when groups are severely underrepresented (Kanter, 1977), males are not likely to be affected because they are unlikely to be a minority in a STEM undergraduate student body. Students at private colleges are expected to have higher persistence rates than those at public colleges. Because of previous mixed findings, no hypotheses are offered for the effects of a college's undergraduate admission rate or the SAT scores of entering undergraduate students on persistence. See Table 1 for a summary of predictions about all individual- and school-level variables.

Multivariate analyses. Due to previous studies' different operationalizations of variables and the use of different sets of variables across studies, it is difficult to predict which variables will remain significant predictors of STEM persistence when they are all entered as predictors in a multivariate model. It is often the case that for a variable of interest, there are studies reporting that it was still a significant predictor of persistence in STEM after considering other relevant variables and other studies reporting that it was not significant in regression models (see, for example, Federman, 2007; Huang et al. 2000). Although I do not have predictions for each variable, I expect the direction of individual- and school-level effects to be the same in multivariate models as previously described.

Additionally, I expect a few predictors to be particularly important. First, because of the role of math ability in one's performance in STEM domains and the role of achievement in providing information about the probability of future success and in limiting a student's major options (e.g., colleges tend to require that students earn above a certain GPA in major-specific courses to be able to earn a degree in that major), SAT-Math, high school achievement, and college STEM grades are expected to be important predictors in multivariate analyses. Strenta et al. (1994) summarized, "Most reviews of these issues…agree that the single most important predictor of choosing a major in science and persisting in it is developed ability or competence" (pp. 514-515). Second, I expect interest to be an important predictor because of its impact on motivation and its tendency to remain significant in regression analyses including many other predictors (e.g., Astin & Astin, 1992; Schaefers et al., 1997). Finally, it is also common for gender differences in STEM entry and persistence to remain after accounting for other relevant predictors (e.g., Huang et al., 2000; Staniec, 2004; Strenta et al., 1994; Tyson et al., 2007; Xie & Shauman, 2003). For example, in a sample of students earning bachelor's degrees, Xie and Shauman (2003) found that women were less likely than men to earn a degree in science or engineering; even when controlling for prior interest, high school math achievement, course taking, grades, SES, and college GPA, the odds of women earning a bachelor's degree in science or engineering were approximately half of the odds of men.

> *Hypothesis 26*: SAT-Math, high school achievement, college STEM grades, interest in STEM, and gender will be important predictors of persistence in STEM majors even when controlling for other individual- and school-level predictors.

Sample differences. These research questions and hypotheses are explored in seven samples of students. The first three samples include high school seniors interested in a STEM major (with analyses being conducted overall and for two subsamples: those choosing a biological science major and those choosing a male-dominated STEM major), and their selection of a major at the end of their second year of college is used to measure persistence. The next three samples include second year college students with a declared STEM major (again with an overall sample and two subsamples being comprised of biological science majors and male-dominated STEM majors), and their declared major at the end of their fourth year of college is used as the indicator of persistence.

These two follow-up time points, the second and fourth years of college, were chosen because of their importance in answering research questions of interest. First, major selection during the second year of college was chosen because that is likely the first major a student has chosen during college, and previous research indicates that much of the STEM pipeline “leak” that occurs in college happens during the first two years (President’s Council of Advisors on Science and Technology, 2012). Gender differences in rates of persistence in STEM also may be larger during the early years of college than during the later years of college. In a large, national sample, Xie and Shauman (2003) found that among high school seniors intending to major in a science or engineering field, 50 percent of males had remained in a science or engineering field during their freshman year of college, whereas only 21 percent of females had remained. Thus, to examine a time that has been identified as a critical period when many students leave the STEM pipeline and when females in particular leave STEM, I examine STEM persistence from high school through the second year of college. Next, because of the importance of earning a degree, I examined STEM persistence through the fourth year of college, when most students complete their degrees. Bachelor’s degrees or higher are required for most STEM jobs in the U.S. (President’s Council of Advisors on Science and Technology, 2012), so attainment of a STEM bachelor’s degree can be viewed as an important accomplishment in the pathway to a STEM career. The final sample includes students who indicated interest in pursuing a STEM major as high school seniors and who declared a college major at the end of their second, third, and fourth years of college. The inclusion of this final, multiple-year longitudinal sample allowed for the exploration of STEM persistence at multiple time points during college.

Interest in exploring whether different variables predict STEM persistence at different time points (e.g., high school through the second year of college versus the second through fourth years of college) was also a factor in creating the different sets of samples. It could be that the predictors identified for use in the present study vary in their ability to predict outcomes at different time points. Due to the temporal lag between the measurement of most predictors (senior year of high school) and the final measurement period in the last four samples (fourth year of college), all predictors may be better indicators in the first three samples (or during earlier years in the longitudinal sample) because the outcome was measured only two years later rather than four years later. Additionally, grades may be better predictors at certain time points due to their use by colleges for admission purposes. Grades may serve as gatekeepers that prevent students from entering or continuing in STEM despite their interest. High school grades may be most important during the transition from high school to college because grades likely play an important role in students’ admission into universities or specific STEM programs within universities. Similarly, college grades may play an important role during the early college years because students may need to apply for admission to specific STEM programs and departments, whose decisions likely rely on prior STEM grades (Brainard & Carlin, 1998). Grades may be less important during the final years of college, when students have already been accepted into their major departments. Gender differences on predictors may also vary in the samples. These differences may be smaller in the samples of second year STEM majors due to additional range restriction; the group of male and female students who have remained in a STEM major at the end of their second year of college may be more similar than the group of males and females who are in high school and indicate interest in majoring in STEM. However, because previous research has tended to focus on STEM persistence at two time points (typically from college entry to the fourth year of college), it is unknown whether any of the predictors used in the current study will show different patterns of results at different time points during college.

Next, because of differences in women's representation within STEM majors, I chose to examine persistence in STEM fields separately for male-dominated and non-male-dominated STEM majors. Some STEM fields are more heavily male-dominated than others, with the biological sciences standing out as being different from other STEM fields in terms of female involvement. For example, using the College & Beyond database that contains SAT scores and majors of students who earned degrees at 12 universities at three points in time, Turner and Bowen (1999) found that even among students with high SAT-Math scores (i.e., > 750), men were more likely than women to choose majors in math, physics, economics, or engineering, whereas women were more likely to choose majors in humanities, psychology, other social sciences, or bio-life sciences. Whereas high ability women may be more likely to choose a major in one particular STEM area (biological sciences), men are more likely to choose a major in all other STEM areas. In the U.S. in 2002, fewer than 20 percent of bachelor's degrees in engineering and fewer than 28 percent of bachelor's degrees in computer science were awarded to women, whereas women earned 61 percent of bachelor's degrees in biological and life sciences (Goan & Cunningham, 2006). Additionally, degree attainment in most STEM fields becomes even more highly male-dominated at higher degree levels, but females remain well-represented in the biological sciences at all degree levels; in 2002, 58 percent of master's degrees and 45 percent of doctoral degrees in biological and life sciences were earned by women (Goan & Cunningham, 2006). Census data on individuals' occupations indicates that women hold less than 25 percent of STEM jobs in the U.S., but this figure varies across STEM fields (President's Council of Advisors on Science and Technology, 2012), with women holding nearly half (44 percent) of jobs in the life sciences, compared to 27 percent of computer jobs and only 13 percent of engineering jobs.

Furthermore, the biological sciences have provided exceptions to typical gender patterns for other predictors used in the present study. For example, males tend to take more advanced high school STEM courses and AP exams than females, but females take more advanced high school biology courses and AP exams than males (e.g., National Academy of Sciences, 2007; Strenta et al., 1994). Similarly, whereas males tend to express more enjoyment of and interest in STEM courses than females, females report being more interested in biology courses than males (e.g., Miller et al., 2006). Some note that biological sciences are more consistent with feminine stereotypes than are other STEM fields. Kulis et al. (2002) noted that “the life sciences may be viewed as more appropriate career choices for women because they relate clearly to nurturing human pursuits that are consistent with traditional gender ideals for women” (p. 665). Biological sciences may also differ from other STEM majors in that students majoring in the biological sciences may be preparing themselves for medical careers. For example, most students who apply to and attend medical school earned undergraduate degrees in the biological sciences (Association of American Medical Colleges, 2011), and most medical fields tend to be gender-balanced or even female-dominated (e.g., Goan & Cunningham, 2006). Therefore, it may be that women are more likely to persist in biological science majors than in male-dominated STEM majors.

Because of the potential differences between the biological sciences and other STEM fields, several analyses are undertaken in the samples of high school seniors interested in STEM and in the samples of second year undergraduate STEM majors. First, where the outcome is persistence in any STEM major, persistence is predicted for only those interested/majoring in biological science majors and for only those interested/majoring in male-dominated STEM majors. Second, persistence in male-dominated STEM fields (rather than in all STEM fields) is predicted for students indicating interest/majoring in these male-dominated STEM fields. When predicting persistence in male-dominated STEM majors, biological science-related predictors are excluded (i.e., when biological sciences are not included in the persistence outcome, they are also excluded as predictors). This could result in more extreme gender differences for some predictors. For example, if females take more courses in biology but males take more courses in all other STEM fields, gender differences in course taking will be larger if biology courses are excluded. Regarding differences in prediction for male-dominated STEM versus all STEM fields, the college-level variable representing the proportion of females in undergraduate STEM departments may be a better predictor in samples where persistence in male-dominated STEM fields is examined; in schools where many STEM majors are male-dominated but biological science majors are female-dominated, the proportion of females may not be representative of the male-dominated majors (i.e., biological sciences may make female representation in STEM look more balanced than it actually is in most STEM majors). The proportion of female undergraduates in STEM may be smaller and a better predictor when persistence in only male-dominated STEM fields is examined.

Contributions of study. The present study contributes to the literature in several ways. First, most research in this area examines entry into the STEM pipeline rather than persistence among those already in the STEM pipeline. For example, some longitudinal samples have followed students from middle school through high school, college, or post-college but included larger populations of students who never intended to earn a degree in a STEM field (e.g., Catsambis, 1994; Maltese & Tai, 2011). Although these studies are useful in predicting high school students' majors, they answer different questions from those of interest in the present study. These studies answer questions related to who enters the STEM pipeline during high school, whereas the present study asks the less studied question of why students who have already entered the STEM pipeline choose to leave.

In their critique of methodological limitations in the literature on women in science, Xie and Shauman (2003) noted that samples are commonly non-representative, non-random, and cross-sectional, and analyses are often not multivariate. The current study overcomes these limitations in several ways. Some studies use single colleges (e.g., Brainard & Carlin, 1998; Deboer, 1986; Ost, 2010; Schaefers et al., 1997), possibly limiting generalizability, but the current study includes a diverse set of colleges that were selected according to a sampling plan, and students from each college who took the SAT and matriculated in that school from 2006 to 2009 were included in the database used for analyses (although the database was further reduced due to missing data, as described in the Method section). The present study's longitudinal nature also makes it unique, with students being followed from high school through the fourth year of college. Although others have used multiple-school or large samples to examine STEM major choice (e.g., Ware & Lee, 1988), it is less common to find that these large-scale studies measure college major at multiple time points during students' undergraduate careers. It is also common to find that few predictors are studied (e.g., Huang et al. 2000; Tyson et al., 2007) or that the effects of multiple predictors are not examined simultaneously (e.g., a regression approach is not used, Chen & Weko, 2009). The present study includes a variety of predictors derived from different theoretical perspectives and includes regression and survival analyses to examine the effects of all predictors while controlling for others. Some predictors are also relatively unique. For example, the use of STEM-specific (rather than overall) GPA is uncommon, but because of its match with the domain, STEM GPA is expected to be a better predictor than an overall GPA across all classes.

Finally, it is rare to find that both individual- and school-level variables are examined together. School-level variables are not often included in studies, and when they are, a multilevel or hierarchical modeling approach is rarely used to account for the clustering of students within colleges (see Smyth & McArdle, 2004, for an exception). The use of single-level models for both individual- and school-level variables violates the independence of observations assumption of many statistical techniques and may result in misestimated standard errors (see Raudenbush & Bryk, 2002). The present study uses a multilevel modeling statistical framework to overcome this methodological issue with some past studies. To summarize, the present study is unique in that it examines a variety of individual- and school-level predictors of STEM persistence at multiple time points during college for over 25,000 undergraduates at nearly 100 four-year colleges and universities in the U.S.

METHOD

Samples

The College Board collected information from students at 108 colleges and universities for a cohort of students beginning college in 2006, from students at 109 schools for a cohort entering college in 2007, and from students at 128 schools for a cohort beginning college in 2008. Schools were selected, based on a sampling plan, to be geographically diverse, include large and small schools, include public and private institutions, and cover a broad range of school selectivity. Data were available through the fourth year of college for the 2006 cohort, through the third year of college for the 2007 cohort, and through the second year of college for the 2008 cohort.

Participants with complete data for all of the measures (described below) were retained for each of seven samples. Additionally, only students who remained in school after the last data collection period were included in the samples (i.e., students in the first three samples returned to school for their third year of college, students in the final four samples either graduated after their fourth year of college or returned to school for a fifth year). Because follow-up information for students who stopped attending a school was unavailable, it was not known whether they dropped out of college completely or transferred to a different college, and if they transferred, what their majors were. Therefore, information about whether these students persisted in STEM was not available, and they were not included in any of the samples described below.

Sample of high school seniors interested in STEM fields. This sample included students who selected a STEM major as one of their intended major choices during high school and who had a reported major at end of their second year of college, a database of 33,884 students at 98 schools. Students from the 2006, 2007, and 2008 cohorts were included in this sample.

Sample of high school seniors interested in biological science fields. This sample included students who selected a biological science major as one of their intended major choices during high school and who had a reported major at end of their second year of college, a database of 7,407 students at 97 schools. Students from the 2006, 2007, and 2008 cohorts were included in this sample.

Sample of high school seniors interested in male-dominated STEM fields. This sample included students who selected a male-dominated STEM major (i.e., within STEM fields other than the biological sciences) as one of their intended majors during high school and who had a reported major at end of their second year of college, a database of 27,288 students at 98 schools. Students from the 2006, 2007, and 2008 cohorts were included in this sample.

Sample of second year undergraduates majoring in STEM fields. This sample included students who had declared a major in a STEM field at the end of their second year of college and who had a reported major at the end of their fourth year of college, a database of 6,191 students at 27 schools. Students from the 2006 cohort were included in this sample, as data from the fourth year of college were not available for students in the 2007 and 2008 cohorts.

Sample of second year undergraduates majoring in biological science fields. This sample included students who had declared a major in a biological science field at the end of their second year of college and who had a reported major at the end of their fourth year of college, a database of 1,809 students at 27 schools. Students from the 2006 cohort were included in this sample.

Sample of second year undergraduates majoring in male-dominated STEM fields. This sample included students who had declared a major in a male-dominated STEM field at the end of their second year of college and who had a reported major at the end of their fourth year of college, a database of 4,382 students at 27 schools. Students from the 2006 cohort were included in this sample.

Multiple-year longitudinal sample. This sample included students who had selected a STEM major as one of their intended major choices during high school and who had reported a major at the end of each of their second, third, and fourth years of college. This sample included 4,906 students at 25 schools from the 2006 cohort.

Measures

Information about participants was gathered through self-report, College Board records, and college records. Self-reported variables were obtained from participants while they were still in high school, at the time they registered to take the SAT. Predictor composites were created based on conceptual similarity, described below. For all composite predictor variables, participants were required to have data for a minimum of one of the variables used to create the composite.

When determining what fields fell into the STEM category for various predictors and for the persistence outcomes, I considered STEM majors to be those "that are traditionally part of natural science divisions: hierarchical, laboratory-based disciplines with several prerequisites, usually including many mathematics courses, and usually with heavy workloads and frequent assignments" (Strenta et al., 1994, p. 520). This includes biological sciences, physical sciences, computer sciences, engineering, and mathematics. Although this definition of STEM is somewhat narrower than some STEM classifications (e.g., those that include non-laboratory sciences such as psychology or other social sciences; United States Immigration and Customs Enforcement, 2012), it is consistent with what others have labeled as "hard sciences" (e.g., Biglan, 1973) and have used when examining STEM versus non-STEM fields (e.g., Astin & Sax, 1996; Hill et al., 2010; Strenta et al., 1994; Xie & Shauman, 2003). Johnson (2011) noted that numerous federal and state legislative actions on STEM entrance and education exclude social science fields from their definition of STEM, providing another rationale for using a narrower definition of STEM such as the one used in the present study.

To verify that the biological sciences are the only STEM majors that should be considered not male-dominated, I used national degree attainment statistics provided by Goan and Cunningham (2006) to determine the proportion of females that earned degrees in each of the five STEM fields. Consistent with Kanter's (1977) identification of tilted proportional representation in groups, I considered male-dominated fields to be those in which fewer than 35 percent of degrees at any educational level were earned by women. According to this definition, only the biological sciences were not male-dominated. As others have noted in their research on STEM fields (e.g., Lips, 1992), biological science stands out as a field that is different from other STEM fields because it is gender-balanced and in some educational settings, female-dominated. The fields of physical sciences, computer sciences, engineering, and mathematics also tended to be male-dominated at the schools included in the present samples; at the majority of schools in both the high school and second year undergraduate samples, females comprised less than 35 percent of the undergraduate student body in these majors.

Analyses in the high school senior samples and in the second year undergraduate samples were conducted where the outcome was retention in any of the five STEM fields for the overall sample, the biological science sample, and the male-dominated STEM sample, and also where the outcome was retention in the four male-dominated STEM fields (i.e., excluding biological science) for those indicating interest/majoring in male-dominated STEM fields. For the multiple-year longitudinal sample, the outcome was persistence in STEM for the overall sample. Predictor and criterion variables used for analyses are described below. Unless otherwise noted, each of the variables described were used in analyses for all samples.

Persistence in STEM. Colleges reported students' majors at the end of their second, third, and fourth years of college. Majors were organized into Classification of Instructional Programs categories (National Center for Education Statistics, 2012), and categories considered to be STEM were: (a) physical sciences, (b) biological and biomedical sciences, (c) science technologies/technicians, (d) computer and information sciences and support services, (e) engineering, (f) engineering technologies and engineering-related fields, and (g) mathematics and statistics. For the samples of high school seniors, persistence was defined as having a declared major in one of these fields at the end of the second year of college; leaving STEM was defined as having a declared major in some other field at the end of the second year of college. For the samples of second year undergraduates, persistence was defined as remaining in a major in one of these fields at the end of one's fourth year of college. Any student who switched to a major outside of these fields at the end of his/her fourth year of college was considered to have left STEM. Similarly, for the multiple-year longitudinal sample, persistence was defined as remaining in one of these majors at the end of each of the second, third, and fourth years of college. For the samples where the outcome of interest was persistence in male-dominated STEM fields, the biological and biomedical sciences category was excluded, as were majors within the science technologies/technicians category that are biological science-based.

SAT-Math and SAT tilt. Official SAT-Math and SAT-Critical Reading scores were obtained from College Board records and were reported on a 200 to 800 point scale. SAT tilt was computed by subtracting a student's SAT-Math score from his/her SAT-Critical Reading score.

High school achievement. Participants provided self-reports of their high school class rank on a 6-point scale (where 1 = lowest fifth, 2 = fourth fifth, 3 = middle fifth, 4 = second fifth, 5 = second tenth, and 6 = highest tenth). Cumulative high school GPA (on a continuous scale from 0 to 4) was obtained from college records; when school-reported high school GPA was unavailable for a participant, his or her self-reported cumulative high school GPA (on an 11-point scale where 0 = F and 4 = A) was used, if available. Participants also self-reported their high school GPAs in both math and natural sciences (on a 5-point scale where 0 = F and 4 = A), which were averaged to create a high school

STEM GPA. High school STEM GPA, high school class rank, and cumulative high school GPA were standardized and averaged to form the high school achievement composite.

High school STEM coursework. Participants reported the number of semesters of high school coursework they had taken in algebra; geometry; trigonometry; pre-calculus; calculus; computer math; other math; chemistry; geology, earth, or space sciences; physics; other natural sciences; and biology, which were summed to compute the semesters of high school STEM coursework. Participants also reported the number of honors/AP courses they had taken in these subjects, which were summed to compute the number of high school STEM honors/AP courses taken. The number of semesters of high school STEM coursework and the number of high school honors/AP courses taken were standardized and averaged to form the high school STEM coursework composite. When the outcome of interest was persistence in male-dominated STEM fields, the high school STEM coursework predictor composite was created without the number of semesters of high school coursework in biology or the number of honors/AP courses in biology.

Self-rated STEM ability. Participants rated both their math ability and their natural sciences ability on a 4-point scale where 1 = below average, 2 = average, 3 = above average, and 4 = highest 10%. The two ratings were averaged to form the self-rated STEM ability composite.

High school interest in STEM. Participants reported a first choice intended college major and up to four additional major choices. Majors falling into five categories were labeled as STEM fields: (a) physical sciences, (b) biological (life) sciences, (c) computer and information sciences and technologies, (d) engineering and engineering technologies, and (e) mathematics. If a participant reported a first choice major in any STEM field, his/her high school interest in STEM was coded as 5; if a participant reported a non-STEM first choice major but a STEM second choice major, his/her interest in STEM was coded as 4; if a participant reported non-STEM majors for the first and second choices but a STEM major for the third choice, his/her interest in STEM was coded as 3, etc. When the outcome of interest was persistence in male-dominated STEM fields, interest in biological (life) sciences was excluded when creating the STEM interest predictor.

High school extracurricular activities and awards in STEM. Participants reported whether they had participated in a math/science or a computer extracurricular activity in each grade of high school, which were summed to compute the number of years of extracurricular activities in STEM. They also reported whether they had received an award or had been an officer in a math/science or a computer activity, which were summed to compute the number of officer positions/awards in STEM. The number of years of extracurricular activities in STEM and the number of officer positions/awards in STEM were standardized and averaged to create the high school extracurricular activities and awards in STEM composite.

Degree goal. Participants reported their ultimate degree goal, which ranged from a specialized training or certificate program to a doctoral or related degree. In the present study, participants planning to earn a graduate degree (either master’s or doctoral) were compared to participants planning to earn a bachelor’s degree.

Race/ethnicity and Gender. Participants reported their gender and race/ethnicity. The racial/ethnic groups examined in the present study were White, Black, Hispanic, Asian, and Other.

Socioeconomic status (SES). Self-reports of three variables were used to create the SES variable: father's education, mother's education, and parents' income. Response options for father's and mother's education ranged from grade school to a graduate or professional degree and were re-coded into a numerical format that quantifies the number of years of education completed. The fifteen response options for parents' income ranged from "less than $10,000" to "more than $200,000," and each response between these two endpoints was a bracket with a $10,000 to $20,000 range of incomes. These income brackets were converted into numerical representations by using the midpoint for each bracket. I then took the natural log of the converted parents' income variable to normalize the distribution. These three variables were standardized and averaged to create the SES variable.

Undergraduate STEM GPA and GPA tilt. Participants' grades in all courses taken during their college career were provided by their colleges. Each course was categorized by the College Board into a broad grouping of courses. All courses falling into the following categories were classified as STEM courses: natural sciences, computer sciences, engineering, and mathematics. Courses falling into the following categories were classified as non-STEM courses: arts and music, business and communications, English, foreign and classical languages, history, humanities, military, health sciences, and social sciences. For the first three samples (high school seniors interested in STEM, biological sciences, and male-dominated STEM fields), GPAs were the credit-hour weighted average course grade obtained during the first year of college, mirroring how GPAs are typically calculated. For the next three samples (second year undergraduates with declared majors in STEM, biological sciences, and male-dominated STEM fields), GPAs were the credit-hour weighted average course grade obtained during the first three years of college. For the multiple-year longitudinal sample, cumulative GPAs were computed at each of three time points: at the end of the first, second, and third years of college. Undergraduate GPA tilt was computed by subtracting STEM GPA from non-STEM GPA.

It should be noted that both of the tilt variables in the present study were created by computing the difference between two separate components (i.e., math ability subtracted from verbal ability, STEM achievement subtracted from non-STEM achievement) and do not reflect students' absolute levels of ability or achievement. For example, a positive score on a tilt variable could result for students with very different levels of ability or achievement, including (a) students with above average ability/achievement in both STEM and non-STEM but higher relative ability/achievement in non-STEM, (b) students with average STEM ability/achievement and above average non-STEM ability/achievement, (c) students with below average STEM ability/achievement and average non-STEM ability/achievement, or (d) students with below average ability/achievement in both STEM and non-STEM but higher relative ability/achievement in non-STEM.

School-level variables. I obtained relevant college-level variables from the Institute of Education Sciences' Data Center (National Center for Education Statistics Institute of Education Sciences, 2012), which provides information about more than 7,000 post-secondary institutions in the United States. Data from 2006, 2008, and 2010 were used. *Public/Private* was a dichotomous coding of a school as public or private. *Cohort SAT* was used as a measure of the ability of a college cohort and was coded as the 25th percentile score on the SAT for entering undergraduate students. *Admission rate* was used as a measure of institutional selectivity and was coded as the number of new undergraduate students admitted to the school divided by the total number of undergraduate applicants. *Proportion females in STEM* was a measure of the extent to which the gender of STEM undergraduates was skewed or balanced and was coded as the proportion of a school's undergraduate STEM student body that was female. This variable was created by summing the total number of female undergraduate students in a school's physical sciences, biological sciences/life sciences, engineering, and mathematics departments and dividing by the total number of undergraduate students in those departments. When the outcome of interest was persistence in male-dominated STEM fields, counts of students in biological sciences/life sciences were not included in calculations. I matched this school-level database to the participant database, so each participant was matched with a full set of school-level variables.

Analyses

Several sets of analyses were run in each of the first six samples described above (i.e., all except the multiple-year longitudinal sample). First, to examine potential differences in persistence within different STEM subfields, I examined persistence rates in the five broad groups of majors that comprised STEM: (a) physical sciences, (b) biological sciences, (c) computer and information sciences, (d) engineering, and (e) mathematics, both overall and by gender. Next, to examine gender differences for predictors and the criterion, male and female means and *SD*s were computed for continuous predictors in each sample, and *d*-values were calculated to quantify gender differences. Frequencies and percentages were used for categorical predictors. To examine the relationship between the predictors and persistence, means, *SD*s, and *d*-values (for continuous variables) and frequencies, percentages, and odds ratios (for categorical variables) were computed for those persisting and for those leaving STEM (or male-dominated STEM) fields. Correlations between all variables were also computed. Relationships between persistence and college-level variables were examined with school-level correlations. Finally, a series of regression models were run to explore the joint effects of the predictors. In the overall and biological science samples, analyses were conducted to predict persistence in STEM. In the samples of students interested in or majoring in male-dominated STEM fields, analyses were conducted with two outcomes: (a) persistence in STEM fields, and (b) persistence in male-dominated STEM fields.

Due to the hierarchical nature of the data (individual students nested within colleges), HLM 6 software (Raudenbush, Bryk, Cheong, & Congdon, 2004) was used for all regression analyses, both individual-level and multilevel, to account for this clustering. The use of a traditional, single-level approach to regression for the present data would violate the regression assumption of independence (because it ignores the clustering that is present) and may lead to inaccurate estimation of standard errors. HLM allows for the inclusion of both individual-level and college-level effects and for exploration of cross-level effects – how variables at one level (e.g., the individual level) affect relationships at another level (e.g., the school-level; Raudenbush & Bryk, 2002).

All individual-level models and multilevel models described below were conducted for eight combinations of samples/outcomes: (a) predicting persistence in STEM majors for high school students interested in STEM, (b) predicting persistence in STEM majors for high school students interested in biological sciences, (c) predicting persistence in STEM majors for high school students interested in male-dominated STEM majors, (d) predicting persistence in male-dominated STEM majors for high school students interested in male-dominated STEM majors, (e) predicting persistence in STEM majors for second year undergraduates with STEM majors, (f) predicting persistence in STEM majors for second year undergraduates with biological science majors, (g) predicting persistence in STEM majors for second year undergraduates with male-dominated STEM majors, and (h) predicting persistence in male-dominated STEM majors for second year undergraduates with male-dominated STEM majors.

Individual-level models. In the first individual-level model, all of the identified individual predictors of persistence were entered as main effects in a logistic regression model where the binary outcome was persisting in or leaving STEM (or male-dominated STEM) fields. Next, because one may be interested in predicting persistence based only on variables that are known at the time students enter college (for prediction purposes), I ran the same logistic regression but excluded the predictors in the model that would not be known at the time of college entry: undergraduate STEM GPA and GPA tilt. Because the outcome was binary (persisting versus not persisting) for these first two models, a hierarchical generalized linear model with a Bernoulli sampling model was used (see Raudenbush & Bryk, 2002, pp. 294-295). The logit link function and population-specific models were used because of interpretability (the coefficients can be interpreted as log odds, which can easily be converted to odds ratios and interpreted as the likelihood of persisting in STEM) and because the resulting coefficients can be interpreted in the same manner as for traditional individual-level logistic regression analyses (the expected change in the outcome associated with a one-unit increase in a predictor, holding constant all other predictors; see Raudenbush & Bryk, 2002, pp. 295-304). Finally, because of the temporal differences in predictors (i.e., most predictors were measured during high school, but undergraduate GPAs were measured during the years following high school), I also examined the effects of all other predictors on undergraduate STEM GPA (which could then affect persistence). Because the outcome was no longer dichotomous, a hierarchical linear model, with a normal sampling model and identity link function, was fit. Predictors were left uncentered because they were generally either dummy coded or else had meaningful zero points. Random effects were included for level 1 intercepts but not slopes.

Multilevel models. Due to the interest in examining school-level variables, I used multilevel modeling for the next set of regression analyses, again using HLM 6 (Raudenbush et al., 2004). First, to determine whether a multilevel modeling approach could be worthwhile, an initial model, an unconditional model with no predictors at either level (where the two levels were represented by individual-level variables and college-level variables), was run. A significant variance estimate in the unconditional model was found for all samples, indicating that between-school variability in STEM persistence was significant and that a multilevel approach could be fruitful. Therefore, the three previously described regression models (using all predictors to predict persistence, using only the predictors known at time of college entry to predict persistence, and using the predictors known at time of college entry to predict undergraduate STEM GPA), with the addition of the four school-level variables and the interaction terms, were run. Random effects were included for level 1 intercepts but not slopes. For purposes of interpreting interactions, the grand-mean centering method described by Enders and Tofighi (2007) and Hofmann and Gavin (1998) was used.

Survival analysis. Although the descriptive statistics calculated for the multiple-year longitudinal sample were similar to those calculated for the six previous samples (e.g., means, *SD*s, *d*-values, counts, and frequencies for predictors by gender; individual- and school-level correlations), the multivariate models differed. Because of its ability to handle time or duration data, survival analysis was used to assess persistence in the multiple-year longitudinal sample. Survival analysis uses logistic regression techniques but allows for the study of the duration of an outcome, for example, allowing one to predict when an outcome will occur or how the probability of an outcome's occurrence changes over time (Wright, 2000). Survival analysis is used in the present study to identify variables associated with survival time, or persistence, in STEM majors.

Right censoring, which happens when an event is not experienced by the time a study ends, was present in the current study because students could have left STEM majors after the final data point was collected. For example, a student who remained in STEM through his/her fourth year of college could have returned for a fifth year of college and left STEM during the fifth year. This would have happened after the final data for the present study had been collected after the fourth year of college. Survival analysis is designed to handle right censored data without bias (Allison, 2010).

Because the exact time of major switching was unknown (i.e., the year in which the major switch occurred was known, but the exact month or day was unknown), a discrete-time method was used; that is, time was measured in intervals rather than as a continuous variable. Two time-dependent predictors (i.e., variables whose values may change over the course of the study) were present: undergraduate STEM GPA and undergraduate GPA tilt. Whereas most predictors remained constant throughout the duration of the study (e.g., high school achievement, gender), undergraduate GPA changed as participants took new classes each school year. Of course, the outcome of STEM persistence could also change over time, as college major choices were reported each year from the second through fourth year of college.

As others have done (e.g., Barber, Murphy, Axinn, & Maples, 2000; Biggeri, Bini, & Grilli, 2001), I used HLM software (Raudenbush et al., 2004) to estimate the multilevel survival models. A three-level model was used when school-level predictors were included, with level 3 including college-level variables, level 2 including individual-level variables that did not vary over time (i.e., those individual-level variables taking on only one value for each individual), and level 1 including individual-level variables that varied over time (i.e., those individual-level variables, such as college STEM GPA, that changed during different measurement periods). A model including only individual-level variables was also run, which was a two-level model that excluded the level 3 school-level predictors. Like the multilevel logistic regression models that were used with dichotomous outcomes in the previous samples, the present survival analyses used a Bernoulli sampling model with logit link function and population-specific models. It should be noted that as a result, the survival models are similar to the logistic regression models used in the other samples, with a few notable differences. First, the multilevel survival model included three levels so that within-person repeated measures could be included at the lowest level, unlike the multilevel logistic models, which had only two levels and no within-person repeated measures. Similarly, models including only individual-level effects were two-level models in the multiple-year longitudinal sample (i.e., constant individual-level predictors at level 2 and repeated measures at level 1) and single-level models in the other samples. Second, time (in years, from the time of the first criterion measurement) was entered as a main effect in survival models; in the present study, potential values that the time variable could take were 0 (for measurements at the end of the second year of college, which was the first measurement period used), 1 (for measurements at the end of the third year of college, one year after the first measurement period), or 2 (for measurements at the end of the fourth year of college, two years after the first measurement period). Finally, the inclusion of the time variable in interaction terms, described below, was unique to the survival models.

In the first set of survival models, a discrete-time form of the standard Cox regression model was used because it does not require assumptions about the distribution of event times (Allison, 2010). Cox regression is based on the proportional hazards model, which assumes that there are no interactions between time and other predictors. Rather than an examination of whether predictor effects vary over time, this analysis is designed to examine whether variables predict the length of time spent in a STEM major. The first set of models included: (a) all individual-level variables predicting persistence, and (b) all individual-level, school-level, and interaction terms predicting persistence. Note that unlike previous samples, no models using only predictors known at the time of college entry were run; because of the focus on predicting persistence throughout college, these models were not run for the multiple-year longitudinal sample. Additionally, because of the possibility that the effects of predictors may change over time (e.g., certain variables may be better predictors at different time points during college), I also ran survival models in which predictor effects were allowed to vary over time. This resulted in a second set of models duplicating the two models in the first set but where every predictor in the model was also included in an interaction term with the time variable. Like previous multilevel models, predictors were left uncentered except for models with interaction terms, where grand-mean centering was used (as described by Enders & Tofighi, 2007 and Hofmann & Gavin, 1998). In all models, random effects were included for level 1 intercepts but not slopes.

RESULTS

Persistence by STEM Subfield

In the sample of high school seniors interested in any STEM major, persistence from high school through the second year of college varied by STEM subfield (see Table 2). The largest persistence rate within any STEM subfield was for the biological sciences, with 36 percent of students who selected a biological science major as one of their top five major choices during high school remaining in a biological science major at the end of their second year of college. The lowest persistence rate within a STEM subfield was for the physical sciences; only 3 percent of students choosing a physical science major during high school selected a physical science major at the end of their second year of college. However, students could choose multiple prospective majors during high school, but only one major per student was obtained at the end of the second year of college. When looking at persistence in any STEM field, persistence rates were highest for high school students interested in computer and information sciences, with 61 percent remaining in a STEM major at the end of their second year of college. STEM persistence rates were lowest for students selecting a physical science major during high school, with only 15 percent remaining in a STEM field at the end of their second year of college. When examining persistence rates for STEM subfields by gender, a few gender differences were found (see Table 3). Whereas females were slightly more likely than males to persist in math majors from high school to the second year of college (20 percent and 16 percent, respectively), males were more likely than females to persist in computer and information sciences (30 percent and 18 percent, respectively) and engineering (38 percent and 6 percent, respectively). Similarly, females who were interested in computer sciences or engineering were less likely than males to continue in any STEM field.

In the sample consisting of undergraduates who were majoring in STEM at the end of their second year of college, persistence rates also varied to some extent by STEM subfield (see Table 4). The lowest persistence rate within a STEM subfield was for math; among those who declared a math major at the end of their second year of college, only 47 percent remained in a math major at the end of their fourth year of college. The highest persistence rate within a STEM subfield was for engineering, with 88 percent of engineering majors persisting from the second through fourth year of college. Similarly, only 9 percent of second year engineering majors switched to a non-STEM major by their fourth year, whereas 26 percent of second year math majors switched to a non-STEM major by their fourth year. Persistence rates by STEM subfield were generally similar for males and females (see Table 5), with the largest differences being found for computer and information sciences (57 percent of males versus 46 percent of females persisting in the major from their second to fourth year of college) and math (43 percent of males versus 52 percent of females persisting in the major through the fourth year of college). Female physical science majors were slightly more likely than males to switch to non-STEM majors by their fourth year, with 22 percent of females and 16 percent of males leaving STEM. On the other hand, female math majors were slightly less likely than males to switch to non-STEM majors by their fourth year, with 23 percent of females and

29 percent of males leaving math for non-STEM majors. Overall, gender differences in persistence by STEM subfield were generally small.

Gender Differences

Generally, patterns of gender differences were quite consistent across samples. The key substantive findings on gender differences for all samples are presented in Table 6. Though not critical to overall substantive understanding, additional descriptive statistics for each sample can be found in Tables 7 through 13. Across samples, effect sizes for gender ranged from quite small (e.g., STEM GPA *d*s < .15 in all samples) to medium (e.g., SAT-Math and self-rated STEM ability *d*s > .50 in some samples; Cohen, 1988).

In the sample of high school seniors interested in STEM, men had higher values than women on SAT-Math, high school coursework in STEM, self-rated STEM ability, high school interest in STEM, and high school extracurricular activities and awards in STEM, as expected (see Table 7). It was also expected that males would have higher degree goals, but this was not the case; males and females were about equally likely to aspire to a graduate degree (66 percent of females and 65 percent of males). Consistent with hypotheses, females had higher SAT tilt (d = -.38), freshman GPA tilt (d = -.11), and high school achievement (though the difference was small: d = -.05) than males. Males were from higher SES families than females (d = .15), and females had slightly higher freshman STEM GPAs than males (d = -.05).

Among high school seniors interested in majoring in biological science fields (see Table 8), gender differences were quite similar to the full sample of high school students interested in any STEM major (compare to Table 7). Males had higher values than females for SAT-Math, high school STEM coursework, extracurricular activities and awards in STEM, and self-rated STEM ability, as predicted. Also consistent with expectations were pro-female gender differences for high school achievement, SAT tilt, and freshman GPA tilt. Males had slightly higher interest in STEM (d = .05), and gender differences on freshman STEM GPA were near-zero (d = .01). No gender differences were found for degree goal, with 78 percent of both males and females planning to earn a graduate degree. Gender differences in persistence were smaller in this biological science sample than in the previous sample including students interested in all STEM majors. In the biological science sample, 58 percent of males and 46 percent of females persisted in STEM through the second year of college, compared to 47 percent of males and 22 percent of females in the sample including students interested in any STEM major.

In the sample of high school seniors indicating interest in a male-dominated STEM field, gender difference hypotheses were supported for SAT-Math, high school STEM coursework, self-rated STEM ability, high school STEM interest (though differences were small, d = .05), high school extracurricular activities and awards in STEM, SAT tilt, and freshman GPA tilt, with males scoring higher than females on all except SAT tilt and freshman GPA tilt (see Table 9). On the other hand, hypotheses about high school achievement and degree goal were not supported. Females were expected to have higher high school achievement than males, but gender differences were near-zero (d = -.01). Males were expected to have higher degree goals, but degree goals were similar across gender, with 63 percent of females and 62 percent of males planning to earn a graduate degree. Males came from higher SES families, and females had higher freshman STEM course grades. Males were more likely than females to persist in both STEM and male-dominated STEM fields. Females had slightly higher persistence rates in any STEM major (14 percent persisted) than in male-dominated STEM majors (10 percent persisted).

In the sample of second year undergraduates majoring in STEM, men scored higher than women on SAT-Math, high school STEM coursework (though differences were small, d = .04), self-rated STEM ability, high school STEM interest, and high school STEM extracurricular activities and awards, as predicted (see Table 10). Opposite of expected, women had higher degree goals than men. Seventy-three percent of females, compared to 66 percent of males, aspired to a graduate degree. As expected, women scored higher than men on high school achievement (d = -.19), SAT tilt (d = -.42), and undergraduate GPA tilt (d = -.24). Gender differences were small for the variables for which I did not have hypotheses: college STEM achievement (d = -.08), and SES (d = .06). The largest gender differences favored males for SAT-Math, high school interest in STEM, and self-rated STEM ability and females for SAT tilt and undergraduate GPA tilt.

Gender differences among second year students with biological science majors (see Table 11) were generally similar to gender differences found in the full sample of STEM majors (compare to Table 10). Notable exceptions included undergraduate STEM GPA, which had a slight pro-female advantage in the full sample (d = -.08) and a slight pro-male advantage in the biological science sample (d = .12), and high school interest, which had a smaller gender difference in the biological science sample (d = .03) than in the full sample of STEM majors (*d* = .37). Both males and females in the biological science sample showed substantially lower high school interest in STEM than those in the full sample. Males and females majoring in a biological science field tended to have higher degree goals than those in the full STEM sample. Persistence rates among males and females were equal in the biological science sample, unlike the full STEM sample, where males were more likely than females to persist.

In the sample of students who selected a male-dominated STEM major at the end of their second year of college, males scored higher than females on SAT-Math, self-rated STEM ability, high school extracurricular activities and awards in STEM, and high school interest in STEM (see Table 12). Contrary to expectations, males were not more likely than females to aspire to a graduate degree (63 percent of males compared to 67 percent of females planned to earn graduate degrees). Consistent with hypotheses, females scored higher than males on high school achievement (*d* = -.26), SAT tilt (*d* = -.25), and undergraduate GPA tilt (*d* = -.17). Females also earned higher college STEM GPAs than males (*d* = -.13). Gender differences were zero or near-zero for high school STEM course taking (*d* = .00 when excluding biological sciences and *d* = -.02 when including biological sciences) and slight for SES (*d* = -.04). Males were more likely than females to persist in any STEM field and in male-dominated STEM fields, though the gender gap in persistence was larger for male-dominated STEM fields.

Gender differences in the multiple-year longitudinal sample were quite consistent with the other samples (see Table 13). Males scored higher than females on SAT-Math, high school interest in STEM, high school STEM coursework (though differences were small, d = .05), extracurricular activities and awards in STEM, and self-rated STEM ability, as expected. Females had higher SAT tilt, high school achievement, and undergraduate GPA tilt. Inconsistent with expectations was the finding that females aspired to higher degree goals than males, with 74 percent of females and 67 percent of males planning to earn a graduate degree. Gender differences in undergraduate STEM GPA were small, but females gained a slight advantage over time; in the first year of college, undergraduate STEM grades were about equal for males and females (d = -.01), which increased slightly in the second year (d = -.06) and again in the third year (d = -.09). Females had lower persistence rates than males at each time point, with persistence rates that were 18 to 20 percentage points lower than persistence rates of males.

Bivariate Predictors of STEM Persistence

Individual-level predictors. Hypotheses about individual-level bivariate predictors of persistence were supported for most variables and in most samples, with only a few exceptions. The direction of findings tended to be consistent across samples, but the magnitude of the effects varied across samples for some predictors (e.g., effect sizes for self-rated STEM ability were positive and large in the high school sample but positive and small in the second year undergraduate sample). Key findings on bivariate predictors of persistence in the high school and second year samples are presented in Table 14. Though not necessary for substantive understanding, additional descriptive statistics for each of these samples can be found in Tables 15 through 22.

Consistent with predictions, persistence in STEM from high school to the second year of college was positively associated with SAT-Math, high school achievement, high school STEM coursework, college STEM grades, self-rated ability in STEM, high school extracurricular activities and awards in STEM, high school interest in STEM, degree goal, and SES in the sample of high school students interested in any STEM major (see Table 15). Also consistent with expectations was that SAT tilt was negatively associated with persistence in STEM; those with relatively strong SAT-Critical Reading scores compared to SAT-Math scores were more likely to leave STEM majors. Freshman GPA tilt was slightly negatively related to STEM persistence (d = -.03). Consistent with prior research, Asian students were more likely than any other racial/ethnic group to persist in STEM majors, with 50 percent of Asian students persisting compared to 32 percent of White, 28 percent of Black, and 27 percent of Hispanic students. Persistence in this sample of high school seniors who intended to major in a STEM field was quite low. Only 33 percent of this sample had declared a STEM major by the end of their second year of college, with the other 67 percent declaring a non-STEM major.

Bivariate relationships between predictors and persistence tended to be smaller in the high school biological science sample (see Table 16) than in the sample of those interested in any STEM major (compare to Table 15), though the direction of effects was generally the same. In the biological science sample, persistence was positively associated with SAT-Math, high school achievement, high school STEM coursework, extracurricular activities and awards in STEM, self-rated STEM ability, freshman STEM GPA, degree goal, and SES. Both SAT tilt and freshman GPA tilt were negatively associated with persistence, as predicted. The relationship between high school interest in

STEM and persistence was near-zero (d = -.01). White students were more likely than Black and Hispanic students and less likely than Asian students to persist in STEM.

The majority of students interested in male-dominated STEM fields during high school had declared a non-STEM major by the end of their second year of college. Only 25 percent persisted in male-dominated STEM majors, and 29 percent persisted in any STEM major. In the comparisons between those who persisted and those who did not, results were similar for persistence in STEM and persistence in male-dominated STEM. The groups of those persisting had higher scores on SAT-Math, high school achievement, high school STEM coursework, self-rated STEM ability, high school STEM interest, high school extracurricular activities and awards in STEM, and freshman STEM GPA, consistent with expectations (see Table 17 and Table 18). Also consistent with expectations was that those who persisted had a more negative SAT tilt, indicating that those who persisted had a stronger tilt toward SAT-Math, whereas those who left had more balanced SAT-Math and SAT-Critical Reading scores. Freshman GPA tilt was small but in the expected direction, with those who left for non-STEM majors having slightly stronger tilt toward non-STEM achievement. Students who persisted in STEM came from higher SES backgrounds than those who did not persist. As expected, Asian students were more likely to persist than any other ethnic group. Males' odds of persisting were more than four times greater than females' odds of persisting in STEM majors and more than six times greater than females' odds of persisting in male-dominated STEM majors, the largest male-to-female odds ratios of all the samples.

Unlike the previous samples, most participants in the sample of second year undergraduates majoring in STEM, 86 percent, persisted in STEM majors. When comparing the group of students persisting in STEM majors to the group leaving STEM majors, the group that persisted scored higher on all continuous predictors except for SAT tilt and undergraduate GPA tilt, though some differences, such as for SES, were small (see Table 19). Hypotheses about SAT-Math, high school achievement, high school STEM coursework, college STEM grades, self-rated ability in STEM, high school interest in STEM, high school extracurricular activities and awards in STEM, and degree goal were supported, as higher scores on these variables were associated with STEM persistence. Relative ability and achievement in non-STEM domains were associated with leaving STEM; those persisting in STEM had more negative SAT tilt and undergraduate GPA tilt (i.e., had stronger STEM ability and achievement relative to non-STEM ability and achievement) than those who did not persist. Persistence rates were similar across ethnic groups. Black students had the lowest persistence rate, 80 percent, and Asian students had the highest persistence rate, 87 percent.

Second year biological science majors were slightly less likely than students in the full STEM sample to persist in STEM from the second to fourth year of college, with 82 percent of biological science majors persisting in STEM majors (compared to 86 percent in the full STEM sample). Like the full STEM sample, biological science majors who persisted in STEM had higher scores on SAT-Math, high school achievement, high school STEM coursework, self-rated STEM ability, high school interest in STEM, and undergraduate STEM GPA than those who left STEM (see Table 20). Additionally, those who left STEM had a more positive SAT tilt and undergraduate GPA tilt (i.e., a tilt toward verbal ability or non-STEM achievement) than those who remained in STEM. One difference was that extracurricular activities and awards in STEM was positively associated with persistence in the full STEM sample (d = .07) but slightly negatively related to persistence in the biological science sample (d = -.04); however, both of these effect sizes are small.

The majority of students in the sample of second year undergraduates with male-dominated STEM majors, 86 percent, remained in male-dominated STEM majors from the second to fourth year of college, and 87 percent remained in any STEM major. Compared to those who left STEM or male-dominated STEM majors, those who persisted scored higher on SAT-Math, high school achievement, high school STEM coursework, college STEM grades, self-rated ability in STEM, high school interest in STEM, extracurricular activities and awards in STEM, degree goal, and SES (see Table 21 and Table 22). Those persisting also had lower SAT tilt and undergraduate GPA tilt, consistent with expectations. Gender differences in persistence were consistent with hypotheses (males were more likely than females to persist), and the disparity between males' and females' persistence rates was larger when predicting persistence in male-dominated STEM than when predicting persistence in all STEM fields. Persistence rates were quite similar across ethnic groups. (A full correlation matrix with individual-level variables for each of the above samples can be found in Table 23 for the high school STEM sample, Table 24 for the high school biological science sample, Table 25 for the high school male-dominated STEM sample, Table 26 for the second year STEM sample,

Table 27 for the second year biological science sample, and Table 28 for the second year male-dominated STEM sample.)

In the multiple-year longitudinal sample of students who showed interest in STEM during high school and remained in college for four years, the largest leak in the STEM pipeline happened between high school and the second year of college, with 38 percent of students leaving STEM by the end of their second year of college. During the third and fourth years of college, fewer students left STEM, with 58 percent persisting from year 2 to 3 and 56 percent persisting from year 3 to 4. Relationships between individual-level predictors and persistence tended to be in the expected direction at all time points (see Table 29).

School-level predictors. Two school-level variables were significantly correlated with persistence in the samples including high school seniors. In the sample of high school seniors interested in any STEM field, at colleges where entering undergraduates had higher SAT scores and at colleges with larger proportions of male STEM undergraduates, students were more likely to persist in STEM majors (see Table 30). In the sample of high school seniors interested in biological sciences, the only school-level variable that was significantly correlated with STEM persistence was cohort SAT (see Table 31). Schools where students earned higher SAT scores had higher STEM persistence rates. In the sample of high school seniors interested in male-dominated STEM fields, two school-level predictors were significantly correlated with persistence in STEM and male-dominated STEM fields (see Table 32). Schools whose entering students had higher SAT scores and schools with higher male representation in undergraduate

STEM majors had higher persistence rates. However, no school-level predictors were significantly correlated with persistence in any of the second year samples (see Table 33 for the sample of STEM majors, Table 34 for the sample of biological science majors, and Table 35 for the sample of male-dominated STEM majors). In the multiple-year longitudinal sample, one school-level predictor was significantly associated with persistence (see Table 36). Cohort SAT was positively associated with persistence in STEM, but the relationship was significant only for persistence through the fourth year of college; at schools where students typically had higher SAT scores, persistence rates in STEM, particularly in the final year of college, were higher.

To summarize the school-level bivariate relationships, in all of the high school samples and in the multiple-year longitudinal sample, schools with higher cohort SAT scores had higher STEM persistence rates. In some samples, colleges with greater male representation had higher STEM persistence rates. College admission rate was not significantly related to persistence in any sample. Additionally, I had expected to find higher persistence rates among students at private colleges than those at public colleges, but this was not the case in any sample.

Multivariate Models with Individual-level Predictors

In the multivariate model including all available individual-level predictors of STEM persistence, several predictors stood out as being important across all samples. Key findings from individual-level multivariate analyses in all samples are presented in Table 37. For additional results from individual-level multivariate analyses in each sample, see Tables 38 through 47 for models predicting persistence with all individual-level variables, Tables 48 through 55 for models predicting persistence with all individual-level variables known at the time of college entry, and Tables 56 through 63 for models predicting undergraduate STEM GPA with individual-level predictors known at the time of college entry.

Models with all individual-level variables. In the sample of high school seniors interested in STEM, all predictors except degree goal, SES, interest, and college STEM GPA were significant predictors of persistence in STEM (see Table 38). The direction of the effects was consistent with the bivariate effects previously discussed, with the exception of three predictors of interest. Whereas freshman GPA tilt was negatively associated with persistence in bivariate analyses, its coefficient was positive in the regression model, indicating that higher tilt toward non-STEM achievement was associated with an increased likelihood of persisting in STEM. Bivariate analyses indicated that Whites were more likely than Blacks and Hispanics to persist, but this effect was also reversed in the regression model, with Blacks and Hispanics being more likely than Whites to persist after accounting for the effects of other predictors. In this regression model, the largest odds ratios were found for gender (odds ratio of 1.96 for male-to-female comparison), SAT-Math (standardized odds ratio of 1.44), and race/ethnicity (odds ratio of 1.59 for Black-to-White comparison, and odds ratio of 1.56 for Asian-to-White comparison).

In the sample of high school seniors interested in biological sciences, several variables were significant predictors of persistence: SAT-Math, high school STEM coursework, extracurricular activities and awards in STEM, self-rated STEM ability, degree goal, gender, race/ethnicity (Black and Asian, compared to White), freshman STEM GPA, and freshman GPA tilt (see Table 39). All but two of these significant coefficients were in the expected direction. Unlike bivariate analyses, the regression coefficients indicated that freshman GPA tilt was positively associated with persistence and that Blacks were more likely than Whites to persist, consistent with findings from the previous sample including all STEM fields.

In the sample of high school seniors interested in male-dominated STEM fields, all predictors except SES and freshman STEM GPA were significant (see Table 40). Similarly, when the outcome was persistence in male-dominated STEM majors, all predictors but SES, freshman STEM GPA, and freshman GPA tilt were significant (see Table 41). Most significant effects were in the expected direction, with the exception of degree goal (a higher degree goal was associated with lower persistence), race/ethnicity (Blacks and Hispanics were more likely than Whites to persist), and freshman GPA tilt (tilt toward non-STEM achievement was positively associated with persistence). The largest effects for both outcomes (persistence in STEM and persistence in male-dominated STEM) were found for gender, SAT-Math, and race/ethnicity (Black-White comparison).

When examining the independent effects of all individual-level predictors on STEM persistence in the sample of second year undergraduates majoring in a STEM field, I found that SAT tilt, high school extracurricular activities and awards in STEM, high school interest in STEM, gender, undergraduate STEM GPA, and undergraduate GPA tilt were significant predictors of persistence (see Table 42). Two significant coefficients had signs that were reversed from bivariate analyses. The high school extracurricular activities and awards in STEM variable was positively associated with persistence in bivariate analyses but had a significant, negative regression coefficient. Undergraduate GPA tilt was negatively related to persistence in bivariate analyses but had a positive regression coefficient. The largest effects were found for undergraduate STEM GPA (standardized odds ratio of 1.90) and gender (male-to-female odds ratio of 1.39).

In the sample of second year biological science majors, only two variables significantly predicted persistence (see Table 43). Undergraduate STEM GPA and undergraduate GPA tilt were both positively associated with persistence. Whereas the positive regression coefficient for undergraduate STEM GPA was expected and consistent with bivariate anlyses, the positive coefficient for undergraduate GPA tilt was not. Undergraduate GPA tilt was negatively associated with persistence in bivariate analyses, such that higher performance in STEM domains relative to non-STEM domains was associated with remaining in STEM majors. This finding was reversed in the regression model, and higher performance in non-STEM domains relative to STEM domains was associated with persistence in STEM.

In the sample of second year students majoring male-dominated STEM fields, significant positive effects were found for high school interest in STEM, gender, and undergraduate STEM GPA, and a significant negative effect was found for SAT tilt in the prediction of both persistence in STEM and persistence in male-dominated STEM (see Table 44 and Table 45). Inconsistent with expectations was a significant negative effect both for the Asian-White comparison and for high school extracurricular activities and awards in STEM in the model predicting persistence in male-dominated STEM fields. Increased participation or awards in STEM activities was associated with decreased persistence in male-dominated STEM majors, and White students were more likely than Asian students to persist in male-dominated STEM fields. The largest effects in both of these models were found for gender and undergraduate STEM GPA.

In the multiple-year longitudinal sample, most predictors were significantly associated with persistence in the hypothesized direction (see Table 46). Exceptions were SES and the Hispanic-White comparison, which were not significant, and undergraduate GPA tilt and the Black-White comparison, with effects that were significant but in the opposite of expected direction. Time had a significant, negative relationship with persistence, with persistence rates decreasing over time. When the survival model including all individual-level predictors was re-run to include interactions between time and each predictor, most interactions were not significant (see Table 47). That is, the effects of most predictors on persistence were consistent throughout college. However, two predictors did interact with time: cumulative STEM GPA and cumulative undergraduate GPA tilt. When students earned high cumulative STEM GPAs, their probability of persistence was consistent across time; however, when cumulative STEM GPA was low, the probability of persistence was lower at later time points in college (see Figure 1). The relationship between grades and persistence became stronger over time. Similarly, the relationship between cumulative undergraduate GPA tilt and persistence became stronger over time, with high relative achievement in STEM becoming more strongly associated with decreased persistence over time (see Figure 2).

Models with individual-level variables known at the time of college entry. When the previously discussed individual-level models were re-run to exclude the predictors not known at the time of college entry (i.e., without undergraduate STEM GPA and undergraduate GPA tilt) results were often very similar. In the high school STEM sample, no substantive changes were found (see Table 48, compare to Table 38). In the high school biological sciences sample, two differences were that in the model including only predictors known at time of college entry, extracurricular activities awards in STEM was no longer significant, and high school achievement became significant (see Table 49, compare to Table 39). In the high school male-dominated STEM sample, one difference was that SES became significant in the model predicting persistence in male-dominated STEM (see Table 50 and Table 51, compare to Table 40 and Table 41). In the sample of second year STEM majors, several changes occurred (see Table 52, compare to Table 42). First, high school extracurricular activities and awards in STEM and SAT tilt were no longer significant predictors of persistence. Second, SAT-Math, high school achievement, and race/ethnicity (the Hispanic-White comparison) became significant predictors. Similarly, in the sample of second year biological science majors, when undergraduate GPAs were removed as predictors, SAT-Math and high school achievement became significant predictors of STEM persistence (see Table 53, compare to Table 43). In the sample of second year male-dominated STEM majors, findings for the models that included only the predictors known at the time of college entry differed from the models including all individual-level predictors in a few ways (see Table 54 and Table 55, compare to Table 44 and Table 45). First, SAT tilt was significant in the models with all individual level predictors, but it was not significant in the models including only the individual-level predictors known at college entry. Second, SAT-Math, high school achievement, and high school STEM coursework were significant only in the models that excluded college GPAs.

Individual-level variables mediated by college GPA. Variables that were significant predictors of persistence only in the models that excluded college GPA were identified as having effects on STEM persistence that were potentially mediated by college GPA. This possibility was explored further by examining a linear regression model where undergraduate STEM GPA was the outcome. Variables that were significant predictors of undergraduate STEM GPA and were also significant predictors of STEM persistence only when undergraduate STEM GPA was excluded as a predictor were identified as being mediated by undergraduate STEM GPA. In the high school STEM sample, no effects were found to be mediated by undergraduate STEM GPA (see Table 56 for linear regression results). In the sample of high school seniors interested in biological sciences, high school achievement significantly predicted freshman STEM GPA (see Table 57). This finding, along with the finding that high school achievement was a significant predictor of STEM persistence only when freshman STEM GPA was excluded as a predictor, suggests that the effect of high school achievement on STEM persistence was at least partially mediated by undergraduate STEM GPA in this sample. In the sample of high school seniors interested in male-dominated STEM fields, no predictors were identified as being mediated by undergraduate STEM GPA (see Table 58 and Table 59 for linear regression results).

In the sample of second year STEM majors, three predictors – race/ethnicity (Hispanic versus White), SAT-Math, and high school achievement – predicted undergraduate STEM GPA (see Table 60), and they significantly predicted STEM persistence only when undergraduate STEM GPA was not included as a predictor, suggesting that undergraduate STEM GPA served as a mediator between these variables and STEM persistence in this sample. In the sample of second year biological sciences majors, SAT-Math and high school achievement were significant predictors of undergraduate STEM GPA (see Table 61) and also predicted persistence only when undergraduate STEM GPA was excluded as a predictor, suggesting that SAT-Math and high school achievement influenced STEM persistence through their effects on undergraduate STEM grades. Similarly, in the sample of second year male-dominated STEM majors, the effects of SAT-Math and high school achievement were mediated by undergraduate STEM GPA (see Table 62 and Table 63 for linear regression results) in the prediction of persistence in both STEM and male-dominated STEM fields. Additionally, undergraduate STEM GPA mediated the effect of high school STEM coursework on persistence in male-dominated STEM fields; high school STEM coursework significantly predicted persistence in male-dominated STEM majors only when undergraduate STEM GPA was not included as a predictor, and it was a significant predictor of undergraduate STEM GPA. To summarize mediator effects, high school achievement and math ability tended to influence persistence in STEM through their effects on college STEM grades, particularly in the samples of second year STEM majors.

Multivariate Models with Individual-level and School-level Predictors

In the multilevel models including all available predictors (individual-level, school-level, and interactions), most school-level predictors were not significant predictors of STEM persistence in most samples. Additionally, most individual-level effects remained consistent with the models that included only individual-level variables. Key findings from multilevel models in all samples are summarized in Table 64. For additional multilevel model results from each sample, see Tables 65 through 74 for models predicting persistence with all individual- and school-level predictors, Tables 75 through 82 for models predicting persistence with all predictors known at the time of college entry, and Tables 83 through 90 for models predicting undergraduate STEM GPA with all predictors known at the time of college entry.

Models with all individual- and school-level variables. In the sample of high school seniors interested in STEM, no school-level main effects significantly predicted STEM persistence (see Table 65). However, the cross-level interaction between an individual's gender and the proportion of undergraduate STEM students that were female did predict persistence in STEM. Both males and females had higher rates of persistence when the proportion of females in STEM was low than when the proportion of females in STEM was high, and males were more likely than females to persist when female STEM representation was low (see Figure 3). All individual-level predictors that had been significant in the model including only individual-level variables (in Table 38) were also significant in this model.

In the sample of high school seniors interested in biological sciences, the only school-level variable that had a significant effect on STEM persistence was the proportion of females in STEM (see Table 66). As in the sample including all high school STEM majors, a significant interaction between school-level female representation in STEM and gender was found (see Figure 4). In this sample, males' persistence rates were similar across different levels of female representation in STEM, but females had higher persistence rates when female representation in STEM was high than when it was low. All individual-level coefficients in this model were consistent with the previously discussed model including only individual-level predictors (in Table 39).

In the sample of high school seniors interested in male-dominated STEM fields, individual-level effects were very similar to models without school-level variables (see Table 67 and Table 68, compare to Table 40 and Table 41). When the interaction between gender and college STEM GPA was added to the model to predict STEM persistence, it became statistically significant (see Figure 5). Whereas females were equally likely to persist in STEM after receiving below or above average STEM grades in college, males were slightly more likely to persist after earning above average than below average college STEM grades. No school-level main effect was significant in these models, and the cross-level interaction between individual gender and school-level female representation in STEM was not significant.

In the sample of second year STEM majors, no school-level main effects were significant predictors of STEM persistence (see Table 69). This is not surprising, considering that no significant bivariate correlations were found. The effects for most individual-level predictors were very similar to the regression model including only individual-level predictors (in Table 42). One exception was for undergraduate GPA tilt, which was significant in the individual-level only model but not in the multilevel model. The cross-level interaction between gender and school-level female representation in STEM was a significant predictor of STEM persistence (see Figure 6). The interaction was disordinal; males were more likely than females to persist in STEM when females' representation at a college was low, but females were more likely than males to persist when the proportion of undergraduate females in STEM was high. However, both males and females became less likely to persist as female representation increased.

In the sample of second year biological sciences majors, only two variables were significant predictors of STEM persistence (see Table 70). Like the individual-only model (in Table 43), undergraduate STEM GPA was positively associated with STEM persistence. Unlike previously discussed models, a college's admission rate was significant in this model, with more selective schools (i.e., those admitting smaller portions of the applicant pool) having higher STEM persistence rates than less selective schools.

In the sample of second year male-dominated STEM majors, no school-level main effects significantly predicted persistence (see Table 71 and Table 72). The cross-level interaction between gender and school-level undergraduate female representation in

STEM was significant only in the model predicting persistence in male-dominated STEM majors (see Figure 7). Both males and females were less likely to persist when female representation in male-dominated STEM fields was high. However, attending a school with a larger female undergraduate presence in male-dominated STEM fields was associated with a higher rate of persistence for females than for males, whereas attending a school with a smaller proportional female representation in male-dominated STEM fields was associated with a lower persistence rate for females than for males. Coefficients for individual-level predictors in these models were consistent with the models that included only the individual-level predictors (in Table 44 and Table 45).

In the multiple-year longitudinal sample, effects from the model including only individual-level predictors remained consistent when school-level predictors were added to the model (see Table 73, compare to Table 46). Additionally, the interaction between school-level female STEM representation and gender was significant. The interaction was disordinal, with females becoming slightly less likely to persist in STEM as their representation increased and males becoming much less likely to persist as female representation in STEM increased (see Figure 8). When all predictors (including individual- and school-level variables, interactions, and interactions with time) were included in the model, several interactions were significant (see Table 74). First, like the prior multilevel survival model without time interactions, the interaction between college-level female representation in STEM and gender was significant (see Figure 9). Whereas males and females were both less likely to persist when female representation in STEM was high than when it was low, the slope was steeper for males. Next, several predictors interacted with time. During the early years of college, persistence rates were similar across schools with different admission rates; however, during the fourth year of college, schools with low admission rates (i.e., more selective schools) had substantially higher persistence rates than schools with high admission rates (see Figure 10). The relationship between college selectivity and persistence was stronger at later time points, and, holding other features constant, less selective schools experienced a large decline in STEM persistence rates from students' early college years to their later college years. Like the model that included individual-level predictors and time interactions (in Table 47), this model also had significant interactions between cumulative STEM GPA and time (see Figure 11) and between cumulative undergraduate GPA tilt and time (see Figure 12).

Models with individual- and school-level variables known at the time of college entry. In the multilevel models including only the predictors known at the time of students' college entry, the same school-level predictors tended to be significant as in the multilevel models including all predictors. Additionally, findings for individual-level variables from the multilevel models including predictors known at the time of college entry were generally consistent with findings from individual-level models including only predictors known at the time of students' entry to college. In the sample of high school seniors interested in STEM, the cross-level interaction between gender and college-level female representation in STEM was significant in the model including only predictors known at the time of college entry, similar to the model including all predictors (see Table 75, compare to Table 65). Males were more likely than females to persist, and the gender gap was largest when female representation in STEM was low (see Figure 13). In the multilevel model that excluded the individual-level predictors not known at the time of college entry, individual-level coefficients were very similar to those in the model that included only individual-level predictors known at the time of college entry for the sample of high school students interested in biological sciences (see Table 76, compare to Table 49). The interaction between the proportion of females in STEM and gender was also significant and very similar to the model including all predictors, supporting the hypothesis about the effects of college-level female STEM representation on females' persistence rates (see Figure 14). For the sample of high school seniors interested in male-dominated STEM fields, no school-level variables were significant predictors of persistence in the model including only those variables known at the time of students' entry to college, consistent with the model including all predictors (see Table 77 and Table 78, compare to Table 67 and Table 68).

In the sample of second year STEM majors, the multilevel model including only predictors known at the time of college entry differed from the multilevel model including all predictors; cohort SAT became significant, with higher school-level SAT scores being associated with lower persistence rates (see Table 79, compare to Table 69). Additionally, SAT tilt and high school extracurricular activities and awards in STEM were not significant, and SAT-Math, high school achievement, and race/ethnicity (the Hispanic-White comparison) were significant in the model including only the predictors known at time of college entry, consistent with the models including only individual-level predictors. The disordinal interaction between gender and school-level female

STEM representation was found in the multilevel model that excluded undergraduate STEM GPA and undergraduate GPA tilt as predictors, consistent with the findings from the model including all predictors (see Figure 15). In the sample of second year biological sciences majors, college admission rate remained significant in the model that excluded undergraduate GPAs as predictors (see Table 80). Additionally, SAT-Math and high school achievement became significant predictors of persistence when undergraduate STEM GPA and undergraduate GPA tilt were not included in the model, consistent with the individual-level model including predictors known at the time of college entry (in Table 53). In the sample of second year male-dominated STEM majors, one difference between the multilevel model including the predictors known at the time of college entry and the multilevel model including all predictors was that one school-level effect, cohort SAT, was significant only in the models including predictors known at college entry (see Table 81 and Table 82, compare to Table 71 and Table 72). Persistence in STEM and male-dominated STEM majors was higher at schools where students had lower SAT scores. The disordinal interaction between gender and female STEM representation was found in the multilevel model that excluded undergraduate GPA in the prediction of persistence in male-dominated STEM majors, consistent with findings from the model including all predictors (see Figure 16).

Variables mediated by college GPA. Findings from the linear multilevel regression models with undergraduate STEM GPA as the outcome confirmed the presence of the previously identified individual-level variables that were mediated by undergraduate STEM GPA. In the high school sample, individual-level effects were very similar to the previously discussed model using only individual-level variables to predict freshman GPA in STEM (see Table 83 for multilevel linear regression results). In the sample of high school seniors interested in biological sciences, high school achievement was a significant predictor of freshman STEM GPA (see Table 84 for multilevel linear regression results) and was a significant predictor of STEM persistence only when freshman STEM GPA was not a predictor, suggesting that the effects of high school achievement on STEM persistence were mediated by freshman STEM GPA in this sample. No mediation effects were found in the sample of high school seniors interested in male-dominated STEM fields (see Table 85 and Table 86 for multilevel linear regression results).

Like the individual-level models, the multilevel models for the sample of second year STEM majors indicated that the effects of SAT-Math, high school achievement, and race/ethnicity (the Hispanic-White comparison) on STEM persistence were mediated by college STEM grades. That is, the effects of these three predictors on persistence were significant only when undergraduate GPA was not included as a predictor, and these predictors were significant predictors of undergraduate STEM GPA (see Table 87). Similarly, in the sample of second year biological science majors, SAT-Math and high school achievement were significantly associated with undergraduate STEM GPA (see Table 88) and were significant predictors of persistence only when undergraduate GPA was not in the model, indicating that their effects on persistence were mediated by undergraduate STEM GPA. In the sample of second year male-dominated STEM majors, the linear multilevel models where undergraduate STEM GPA was the dependent variable (see Table 89 and Table 90) again provided support for the mediating role of undergraduate STEM GPA. Both SAT-Math and high school achievement influenced persistence in STEM and male-dominated STEM via their effects on undergraduate STEM grades. Undergraduate STEM GPA served as a mediator between high school STEM coursework and persistence when the outcome included only male-dominated STEM fields.

DISCUSSION

Persistence Rates across Samples

Overall, persistence in STEM was quite high in the samples of second year college students (approximately 86 percent persisted in STEM majors from the second to fourth year of college) and was low in the samples of high school students (33 percent of students persisted in STEM from high school to the second year of college). STEM persistence in the multiple-year longitudinal sample fell in between these two samples, with 62 percent of students persisting from high school to the second year of college, 58 percent persisting through the third year of college, and 56 percent persisting through the fourth year of college. These differences have several possible explanations.

First, the high school and multiple-year longitudinal samples included students indicating any interest in STEM during high school, even if a STEM major was not their first choice major. Therefore, although all students showed some interest in STEM majors, some of these students were likely already more committed to non-STEM majors. All students in the second year sample had selected a STEM major at that time point, so it makes sense that this group was more committed to a major choice and had a higher persistence rate than the other samples.

Second, previous research indicates that it is not entirely unexpected that such a large portion of the sample left STEM during the first two years of college, as much of the STEM pipeline leak occurs during the early college years (President's Council of Advisors on Science and Technology, 2012). In a single-institution longitudinal study that followed college students from freshman through senior year, Stinebrickner and

Stinebrickner (2011) found that when selecting majors at college entry, students were quite uncertain about their choices; when freshmen were asked to estimate the probability of graduating with a degree in their first choice major rather than another major, the average estimate was .60. Participants estimated the probability of earning a degree in their first choice major in this way at six time points throughout college, and for those initially interested in STEM fields, the estimated probability of choosing a STEM major declined sharply between the first and second years of college. This decline during the first two years of college was steeper for STEM than for any other category of major. During later years, probability estimates remained more stable, indicating that most students who left STEM fields did so during their early years of college. These findings are consistent with the present study, as major choice appeared quite stable by the time students had completed their second year of college.

Third, the high school sample differed from the multiple-year longitudinal and second year samples in that the high school sample had remained in school through the third year of college, whereas the other groups had remained in school through the fifth year of college or had graduated. The high school sample included students who may have dropped out of college at some point during their third year or later (although this information was generally not available), whereas the other samples included students who were close to earning a degree or who had earned a degree. This feature of the samples may have made them different in terms of their ability and motivation to complete college in any major and could contribute to sample differences in persistence rates.

Finally, differences between the high school and multiple-year longitudinal samples could be caused by the inclusion of different schools in the samples. To explore this possibility, the high school analyses were re-run in a reduced sample including only those schools that appeared in the multiple-year longitudinal sample (see Appendix A). In this reduced high school sample, 42 percent of students persisted in STEM from high school to the second year of college, an increase over the 33 percent persistence rate in the full high school sample. However, the persistence rate of 62 percent from high school to the second year of college in the multiple-year longitudinal sample was still substantially higher than persistence among those in the reduced high school sample that included the same colleges, indicating that persistence rates may have been lower in the high school sample because it could have included students who were less academically prepared, motivated, etc., to complete a college degree in any field and who ultimately dropped out of college. In the reduced sample, females were somewhat more likely to persist in STEM through the second year of college than in the full sample (27 percent in the reduced sample persisted, compared to 22 percent in the full sample, see Table A2); However, this rate was still very different from the multiple-year longitudinal sample, where 50 percent of females persisted in STEM through the second year of college. The inclusion of different schools in the multiple-year longitudinal and high school samples accounted for some of the difference in persistence rates, but large differences in persistence between the high school and multiple-year longitudinal samples remained even when the samples included the same group of colleges. Additionally, substantive conclusions drawn from analyses in the full high school sample were generally consistent with those drawn from the reduced sample (with the exception of STEM interest in high school, which was a significant predictor of STEM persistence in multivariate analyses in the reduced sample but not in the full sample; see Tables A5 and A8). It was concluded that the inclusion of different colleges in the high school and multiple-year longitudinal samples was not the main cause of differences between samples.

Gender Differences

Hypotheses about gender differences were supported in most samples for predictions about persistence rates (Hypothesis 1), SAT-Math (Hypothesis 2), high school achievement (Hypothesis 4), high school STEM coursework (Hypothesis 8), self-rated ability in STEM (Hypothesis 10), high school interest in STEM (Hypothesis 12), high school extracurricular activities and awards in STEM (Hypothesis 13), SAT tilt (Hypothesis 16), and undergraduate GPA tilt (Hypothesis 17). No support was found for the hypothesis regarding degree goal (Hypothesis 20). Findings for each variable are discussed in turn below.

Persistence. As predicted, females typically had lower STEM persistence rates than males. Gender differences in persistence were larger in the sample of high school students interested in STEM than in the sample of second year STEM majors, suggesting that the largest disparity in terms of males' and females' persistence in STEM happens during the early years of college. Females' low STEM persistence rates from high school to the second year of college compared to their much higher persistence rates from the second to fourth year of college suggests that the early years of college may be a critical time when many women leave the STEM pipeline. Early college experiences may lead many more females than males to determine that a STEM major is not for them. Persistence rates in the multiple-year longitudinal sample generally supported this idea, with the largest loss of women in STEM happening between high school and the second year of college. Students who had declared STEM majors by the end of their second year of college, both males and females, were a more committed group in general, with little attrition during the third and fourth years of college.

Gender differences in persistence were smaller among those interested in or majoring in biological science fields than in male-dominated STEM fields. In the high school sample, 46 percent of high school females who were interested in a biological science field continued in STEM through the end of the second year of college, whereas only 14 percent of high school females interested in a male-dominated STEM field continued in STEM through the second year of college. Consistent with previous findings indicating that the biological sciences differ from male-dominated STEM fields in terms of female involvement and interest (e.g., Miller et al., 2006; Turner & Bowen, 1999), the present results, particularly from the high school sample, suggest that the loss of women from the STEM pipeline is more severe in male-dominated STEM fields. Extra pressures of male-dominated environments may prevent more women than men from persisting in these STEM fields. Additionally, the only sample for which gender differences in persistence became nonsignificant in a multivariate model was the sample of second year students majoring in a biological science field. For all other samples, gender effects remained significant even after accounting for all of the individual- and school-level predictors available in the present study.

SAT-Math. Consistent with past research, females in the present samples earned lower average SAT-Math scores than males in those samples. Although mean gender differences may be small for some math ability tests taken by nationally representative samples (see Friedman, 1989), non-trivial gender differences were found in the present study. Among high school seniors who showed interest in STEM majors, males scored over one-half of a standard deviation higher on the SAT-Math test, on average, than females. Students in the samples of second year college students who had declared STEM majors had higher SAT-Math scores than those in the samples of high school students interested in STEM fields, and gender differences were smaller in the second year undergraduate samples than in the high school samples. This reduction in gender differences may be due to ability-related attrition that occurs during the first two years of college. Because of the challenges associated with persisting in STEM during the first two years of college, those who do manage to remain in STEM are a higher ability group than those who leave STEM, and there are smaller gender differences in these more restricted groups.

High school achievement. Also consistent with expectations was the finding that females tended to earn better grades in high school than did males. Gender differences were often small in the high school samples but became larger in the samples of second year undergraduates majoring in STEM or male-dominated STEM fields. That is, in the group of students who declared a STEM major during their second year of college, females had earned higher grades in high school than males, whereas in the group of high school students interested in STEM, males and females had earned more similar grades in high school. On average, the group who declared STEM majors during the second year of college was a higher achieving group (in terms of high school grades) than the group of high school seniors indicating interest in STEM.

College STEM achievement. It was not clear whether this female advantage in grades would be maintained after accounting for course taking patterns (i.e., when examining grades in STEM courses only), and no consistent gender differences in undergraduate STEM GPA were found in the present study. Across samples, gender differences in undergraduate STEM GPA varied in direction and were small. Males in the biological science samples earned slightly higher STEM GPAs than females, whereas in the other samples, females earned higher STEM GPAs than males. This finding is not consistent with the idea that women have higher achievement in biological science fields, though the effect sizes indicate that overall, gender differences in college STEM grades were not large. The largest gender difference was found for the sample of second year students with male-dominated STEM majors, where females earned STEM GPAs that were .13 of a standard deviation higher than males. It may be that examining only STEM course grades rather than all course grades leads to a reduction in gender differences due to different course taking patterns. If one were to consider only overall college GPA, gender differences may be larger than if one considered STEM courses only, which are most relevant to the research questions at hand.

Self-rated STEM ability. Several researchers have discovered gender differences in self-rated ability, particularly in math and science domains, with females evaluating themselves more negatively (e.g., Felder et al., 1995; Pryor et al., 2009). The present study's results confirmed this finding; males in all samples had higher self-rated math and science ability than females. In the samples of high school students, males' self-ratings were approximately one-half of a standard deviation higher than females', and gender differences were smaller in the samples of second year undergraduates. Students with lower self-rated ability may have tended to leave STEM before they declared a major during their second year of college, leaving a group of students with higher domain-relevant self-efficacy in the second year sample, compared to the high school sample. Gender differences in self-rated ability may reflect not only gender differences in cultural messages or in appraisal tendencies (e.g., Astin & Sax, 1996; Deboer, 1986) but also gender differences on other variables measured in the present study, such as math ability and interest. The magnitude of gender differences in self-rated STEM ability was very similar to the magnitude of gender differences in SAT-Math, so the mean gender differences in self-ratings of ability tended to mirror mean gender differences in measured ability.

High school STEM interest. Others have found that even in samples of students who show interest in STEM majors or careers, males tend to show more interest in STEM than females (e.g., Ware et al., 1985). This finding was confirmed in the present study, though differences were often quite small, particularly in the high school senior samples. Overall interest in STEM was substantially higher among the sample of high school seniors than among the sample of second year undergraduates, indicating that the high school seniors were more likely to have selected a STEM major as their first choice major. High rates of major switching during the first two years of college may account for this finding, as many high school students with interest in STEM did not pursue STEM majors two years later. More than 67 percent of students in the present samples of high school seniors did not persist in STEM majors at the end of their second year of college, so many who had selected a STEM major as their first choice major during high school did not pursue a STEM major at all. The second year college sample included students who had passed this phase of high major switching and had settled on STEM majors, even though their interest in STEM may not have been strong during high school. Males in the sample of second year STEM majors indicated higher interest in STEM than females by just over one-third of a standard deviation, whereas males in the sample of second year male-dominated STEM majors indicated higher interest in male-dominated STEM than females by nearly one-half of a standard deviation. These gender differences were larger for the second sample because of the exclusion of biological sciences, a major that is often female-dominated (Sax, 2008). Gender differences in interest for the second year biological science sample were very small, with a *d*-value of only .03, supporting the idea that the biological sciences show smaller gender differences in interest than other STEM fields.

High school extracurricular activities, awards, and officer positions in STEM. Extracurricular activities and awards in STEM were included as indicators of STEM interest and involvement, and the expected pattern of findings was found for this variable. Namely, males in all samples had higher participation in extracurricular activities, including holding officer positions, and had earned more STEM-related awards than females. Consistent with stereotypes, males were more likely than females to be involved with high school math, science, and computer clubs. Gender differences were largest in the high school samples; in the full high school STEM sample, males outscored females by nearly one-third of a standard deviation. In the sample of second year undergraduates majoring in any STEM field, males outscored females by only .14 of a standard deviation. Differences between the high school and second year college samples may again be due to attrition during the first two years of college that led to a more restricted sample of students in the second year sample. Gender differences were smaller for high school students interested in biological science majors than for those interested in male-dominated STEM majors. High school females interested in biological sciences tended to be more active in extracurricular activities and to earn more STEM awards during high school than females interested in male-dominated STEM fields. This may be a reflection of women's tendency to be more interested in and invested in biological science fields.

Relative non-STEM ability and achievement. Some have found that females have higher relative ability and achievement in certain non-STEM domains than males (e.g., Hyde & Linn, 1988), which may explain females' reduced STEM persistence; the findings in the present study provided support for this idea. It should be noted that different patterns of STEM and non-STEM ability and achievement could lead to similar gender differences in tilt. For example, females could be found to have a more positive tilt than males if (a) both males and females have stronger relative STEM to non-STEM ability/achievement but the difference between non-STEM and STEM ability/achievement is smaller for females than for males, or (b) both males and females have stronger relative non-STEM to STEM ability/achievement but the difference between non-STEM and STEM ability/achievement is larger for females than for males. In the present samples, scenario *a* was found for SAT tilt, and scenario *b* was found for undergraduate GPA tilt. Males tended to have higher SAT-Math scores, relative to SAT-Critical Reading scores, than females. Males had a larger disparity between SAT-Math and SAT-Critical Reading (with higher SAT-Math scores), whereas females had more balanced SAT-Math and SAT-Critical Reading scores (with slightly higher SAT-Math scores). Females also had a more positive undergraduate GPA tilt, indicating that females had higher non-STEM undergraduate GPA relative to STEM GPA than males, but the pattern of scores was different from SAT tilt. Whereas both males and females in the samples generally had higher relative STEM ability (i.e., both groups tended to have higher SAT-Math relative to SAT-Critical Reading scores, but the disparity was larger for males), both males and females had higher relative non-STEM achievement during college (i.e., all students tended to earn higher non-STEM than STEM grades, but the difference between non-STEM and STEM grades was larger for females). This finding is likely a feature of different grading standards across academic departments, with STEM courses being known for having harsher grading standards. Nevertheless, females tended to have higher relative non-STEM ability and achievement than males, which may have made females more likely to believe that they were better suited for non-STEM majors.

Gender differences in tilt, both SAT tilt and undergraduate GPA tilt, were larger in the second year compared to the high school sample. However, in the multiple-year longitudinal sample, gender differences in undergraduate GPA tilt remained steady across college. Additionally, gender differences in undergraduate GPA tilt were larger in the biological science samples than in the male-dominated STEM samples. Females in the biological sciences tended to have stronger SAT tilt and GPA tilt toward non-STEM ability and achievement than females in male-dominated STEM fields, indicating that students with different relative abilities and skills choose to enter different STEM subfields.

High school STEM coursework. Similar to others who have found only small gender differences in science and math high school course taking (e.g., Farmer et al., 1995), I typically found only small differences in the number of STEM-related high school courses taken by males and females. In most samples, males had taken more math and sciences courses than females, but differences were often small. The largest gender differences in course taking were found for the sample of high school seniors interested in male-dominated STEM fields, where males had taken nearly one-fourth of a standard deviation more STEM-related classes in high school than females. Smaller gender differences for the sample of high school students interested in the biological sciences, compared to those interested in male-dominated STEM fields, suggest that females' investment in STEM via course taking may vary by STEM subfield. Again, gender differences were smaller in the samples of second year undergraduates than in the high school samples, which may be related to the fact that the second year sample is a more restricted group (e.g., more highly prepared, higher ability) than the sample of high school seniors. Although in past decades large gender differences in science and math course taking during high school may have been an important factor in the gender differences in STEM persistence (e.g., Goldin et al., 2006), gender differences in the present samples were small, suggesting that STEM-related course taking in high school does not play a large role in causing gender differences in STEM persistence among students who are interested in STEM.

Degree goal. Several previous studies indicated that in samples of students intending to pursue STEM careers, males were more likely than females to plan to attend graduate school (e.g., Farmer et al., 1995; Felder et al., 1995). Findings from the present study were not consistent with these findings. In all samples, females were either approximately equally or even more likely than males to intend to pursue graduate degrees. Males are more likely than females to earn master's and doctoral degrees in most STEM fields (Goan & Cunningham, 2006), so it seems that many undergraduate females in STEM who aspire to graduate degrees may forgo their goals of attending graduate school or may switch to non-STEM fields for graduate studies.

Race/ethnicity and SES. Gender differences on race/ethnicity and SES were not hypothesized, but a few differences were noted. Ethnic identification was quite similar for males and females in the samples of high school students, with the largest gender differences being that a larger proportion of males than females identified as Asian and a larger proportion of females than males identified as Black. In the samples of second year college students, a larger proportion of males than females were White and a larger proportion of females than males were Black or Asian. Differences in SES were small, with males coming from slightly higher SES families in all samples except the sample of second year students majoring in male-dominated STEM majors. Overall, gender differences in race/ethnicity and SES were quite small.

Summary of gender differences. Although the gender differences discussed above are often found in nationally representative samples (e.g., Huang et al., 2000), it is more striking that they remained in samples of high school seniors interesting in pursuing STEM majors as well as in samples of undergraduates who had completed two years of college and had chosen a STEM major. Gender differences varied between high school seniors and second year undergraduates in that smaller gender differences were found for several variables in the samples of second year undergraduates than in the samples of high school seniors. This was hypothesized to be due to the restricted nature of the second year undergraduate sample (e.g., those who scored very low on ability, achievement, or preparation predictors had likely not been able to remain in STEM for very long). The sample of second year undergraduate STEM majors was a more academically able and prepared group than the sample of high school seniors interested in STEM.

Separating the biological sciences and male-dominated STEM fields sometimes had an impact on gender differences but it was not always in the expected direction and was not always a consistent effect for the high school and second year samples. For example, gender differences on SAT-Math and high school STEM coursework were smaller for the high school biological science sample than for the high school male-dominated STEM sample; this pattern was reversed for the second year undergraduate sample, with larger gender differences for the biological science sample than for the male-dominated STEM sample. In the cases where gender differences were larger for those interested in or majoring in male-dominated STEM fields than for those interested in or majoring in biological sciences, this was hypothesized to be due to the female “advantage” for the biological sciences in terms of course taking and interest. That is, females tend to be more interested in and to take more courses in biological sciences than males, so removing biological sciences led to increased *d*-values favoring males in some cases (e.g., high school STEM coursework in the high school senior sample, high school STEM interest for the sample of second year undergraduates).

Gender differences may help to explain some of the gender disparity in STEM persistence, as males were more likely than females to persist in STEM in most samples in the present study. Males scored higher on several predictors that were positively associated with persistence, providing a partial explanation for why males were more likely than females to persist in STEM. On the other hand, gender differences favoring females for predictors that were positively associated with persistence (e.g., undergraduate STEM GPA) would not account for gender differences in persistence and could make the effect of gender larger. The relationship between all of the above-discussed predictors and persistence in STEM are discussed in the following section.

Individual-level Predictors of Persistence in STEM Majors

Results for most bivariate relationships between predictors and persistence were consistent with expectations. Hypotheses about the positive relationship between persistence and SAT-Math (Hypothesis 3), high school achievement (Hypothesis 6), college STEM grades (Hypothesis 7), high school STEM course taking (Hypothesis 9), self-rated STEM ability (Hypothesis 11), and SES (Hypothesis 22) were supported in all samples. The predicted negative relationships between persistence and SAT tilt (Hypothesis 18) and undergraduate GPA tilt (Hypothesis 19) were also supported in all samples. Relationships between persistence and high school interest in STEM (Hypothesis 14), extracurricular activities, awards, and officer positions in STEM (Hypothesis 15), degree goal (Hypothesis 21), and race/ethnicity (Hypothesis 23) were supported in all but one sample for each predictor. Results from multivariate models were more complicated, with each predictor being significant in a model for at least one sample. Bivariate and multivariate results for each predictor are discussed below.

SAT-Math. As predicted, math ability, as measured by the SAT-Math test, was an important predictor of persistence in STEM. In bivariate analyses for all samples, SAT-Math had one of the largest effect sizes. For example, among high school seniors interested in STEM majors, those who persisted in STEM majors two years later had SAT-Math scores that were over three-fourths of a standard deviation higher than students who chose non-STEM majors.

In multivariate analyses including other predictors, SAT-Math remained an important predictor of persistence. SAT-Math was a significant predictor of persistence in all samples, either directly or indirectly through undergraduate STEM GPA. SAT-Math was a better predictor (i.e., had a larger regression coefficient and odds ratio) in the samples of high school students than in the samples of second year undergraduates. This seems reasonable due to the temporal differences in the predictor-criterion measurements for the two samples; SAT-Math was measured two years prior to the persistence measurement in the samples of high school students but four years prior to the persistence measurement in the samples of second year college students. It also seems more likely that external decision makers would use SAT-Math scores earlier in college rather than later in college, so the gate keeping function of SAT scores would be more likely to occur in the sample of high school students. For example, SAT-Math scores may be used for the purpose of admitting students to particular majors, which is more likely to occur during the earlier college years than during the later college years. Therefore, the relationship between SAT-Math and persistence may be stronger in the high school sample because scores are used both by students (e.g., to assess the probability of success in STEM) and by external decision makers to determine persistence in STEM. Smaller SAT-Math coefficients for the second year undergraduate samples also may be due to attrition that took place during the early college years, with lower ability students disproportionally leaving STEM, resulting in a higher ability second year undergraduate sample with smaller variance in math ability. The temporal differences between predictors and criterion measures for different samples may also explain why SAT-Math had a direct effect on persistence in the high school samples but an indirect effect in the second year undergraduate samples; as more time passed, math ability exerted its influence on STEM persistence through college achievement rather than directly. Within the high school sample, SAT-Math was a better predictor in analyses examining male-dominated STEM majors than in analyses examining biological science majors. It may be that there are more math requirements in male-dominated STEM majors such as engineering (or mathematics, of course) than in the biological sciences. Across samples, the present study identifies math ability as an important predictor of STEM persistence throughout college, even when other important predictors are considered.

High school achievement. As a reflection of ability as well as non-cognitive attributes such as motivation and study habits, high school grades were expected to predict persistence in STEM. This prediction that high school achievement would be associated with STEM persistence was confirmed in bivariate analyses. In all samples, those who persisted in STEM had high school achievement scores .25 to .42 of a standard deviation higher than those who did not persist in STEM.

In multivariate analyses for the overall and male-dominated STEM high school samples and the multiple-year longitudinal sample, high school achievement significantly predicted persistence in STEM. In the other samples, high school achievement predicted persistence only when college grades were excluded as predictors. Because high school achievement was found to be a strong predictor of undergraduate STEM GPA and because the effect of high school achievement on STEM persistence became nonsignificant when undergraduate GPA was added as a predictor, high school achievement is seen as being mediated by undergraduate STEM GPA in these samples. That is, high school achievement affects persistence in STEM via its effect on college STEM achievement. This mediating effect may not have been found in most of the high school samples because only one year of college grades was used to represent college achievement for these samples (compared to three years of college grades in the second year undergraduate samples) and because high school achievement was closer in time, and perhaps more relevant, for the high school samples. That is, as students get further removed from high school, their high school grades may become less important as direct predictors of persistence in STEM but may remain important as indirect predictors of STEM persistence. Nevertheless, high school grades were important predictors of STEM persistence in all samples, either directly or indirectly through undergraduate STEM GPA.

College STEM achievement. Undergraduate STEM GPA was also an important predictor of persistence, particularly in the samples of second year undergraduate STEM majors. In these samples of second year STEM majors, bivariate analyses indicated that undergraduate STEM GPA was the best predictor of persistence in STEM, compared to other continuous predictors. This effect was also found but was smaller in the sample of high school students, which is likely partially due to the fact that first year undergraduate STEM grades were used in this sample, whereas three years of undergraduate STEM grades were used in the second year undergraduate sample. Because college STEM achievement represented two additional years of course grades in the second year undergraduate samples, it was a more reliable, longer term measure of college STEM achievement than was used in the high school samples.

For multivariate analyses in the samples of second year college students, undergraduate STEM GPA was the best predictor of persistence, compared to all other available predictors (i.e., the regression coefficient and odds ratio were larger for undergraduate STEM GPA than for any other predictor). It was also one of the best predictors in the multiple-year longitudinal sample. However, in the samples of high school students, undergraduate STEM GPA regression coefficients were nonsignificant in all samples except for the biological science sample. The survival model that included interactions between all variables and time for the multiple-year longitudinal sample also confirmed the finding that undergraduate STEM GPA was more strongly related to STEM persistence during later years of college than during earlier years of college. As a longer term measure of academic performance in STEM, undergraduate STEM GPA was one of the best predictors of persistence among second year college students with STEM majors. As a measure of first year grades in STEM, undergraduate STEM GPA was not as important in samples of high school students.

Because males and females have been found to make different attributions for their successes and failures, I expected to find an interaction between gender and undergraduate STEM grades. Females tend to attribute their failures to a lack of ability whereas males tend to attribute their failures to external features (e.g., Felder et al., 1995), so I expected to find the largest difference between males' and females' persistence rates when college STEM grades were poor, with females hypothesized to be more likely than males to leave STEM after earning poor STEM grades (Hypothesis 5). However, this prediction was not supported in any sample. The interaction was significant in the high school male-dominated STEM sample in the prediction of persistence in STEM, but the largest gender differences in persistence were found when STEM grades were high rather than when STEM grades were low. Thus, the hypothesis regarding the interaction between college STEM grades and gender was not supported. More direct measures of attributions about course grades (e.g., why students believed they performed poorly in STEM courses, attributional tendencies) may have been more likely to provide support for this idea, but such measures were not available in the present study.

High school STEM coursework. As an indicator of prior preparation and investment in STEM, high school course taking in science and math was expected to predict persistence in STEM majors. Bivariate analyses indicated that this was the case in all samples, as those who persisted in STEM had taken more STEM-related courses and honors courses in high school than those who did not persist in STEM. This effect was larger in the high school senior sample (where those who pursued a STEM major scored over one-half of a standard deviation higher than those who pursued a non-STEM major) than in the second year undergraduate sample (where those who persisted in STEM scored nearly one-fourth of a standard deviation higher than those who did not persist).

In the high school samples and the multiple-year longitudinal sample, high school STEM coursework was a significant predictor of persistence in multivariate analyses, confirming the importance of high school course taking. As others (e.g., Sherman, 1982) have suggested, science and math course taking in high school may serve as a "critical filter" that limits the possibilities for pursuing STEM majors among those with deficient high school preparation. Nevertheless, course taking was not as important as other factors such as math ability and self-rated STEM ability in the present samples of high school seniors. Additionally, high school coursework in STEM was not significant in regression analyses including all predictors for most samples of second year undergraduate STEM majors. This finding may be due to the decreased importance of high school course taking by the time one reaches the later college years. In the sample of second year undergraduates with male-dominated STEM majors, high school STEM coursework was a significant predictor only in the regression model that excluded undergraduate GPA in the prediction of persistence in male-dominated STEM majors. This finding, along with the finding that high school STEM coursework predicted undergraduate STEM GPA, led to the conclusion that undergraduate STEM GPA mediated the relationship between high school STEM coursework and persistence in male-dominated STEM fields. It is not clear why high school STEM coursework was more important in the second year undergraduate sample of male-dominated STEM majors than in the other second year samples. Perhaps high school math and science courses are more relevant and/or critical for male-dominated STEM major coursework than for biological science major coursework during college. To summarize, for high school seniors interested in STEM, high school STEM course taking was a significant, independent predictor of choosing a STEM major two years later. On the other hand, for second year undergraduate STEM majors, high school STEM course taking appeared to have a nonsignificant or else only an indirect effect (through college STEM grades) on persistence in STEM.

Self-rated STEM ability. Due to previous research on the role of self-rated ability on career choice and persistence, I hypothesized that self-rated ability in STEM would predict persistence in STEM majors. Bivariate analyses supported this prediction, with those in the high school senior sample who persisted in STEM scoring three-fourths of a standard deviation higher on self-rated STEM ability than those who did not persist. This effect was smaller in the samples of second year undergraduates and in the multiple-year longitudinal sample; the self-rated STEM ability difference between those persisting in and those leaving STEM was closer to one-third of a standard deviation in these samples. Self-rated STEM ability also had a weaker relationship with persistence in the biological sciences samples than in the male-dominated STEM samples; perhaps self-rated math and science ability is more important in male-dominated STEM majors because of heavier math course loads required in these domains.

Self-rated ability in STEM was a significant predictor of persistence in multivariate analyses in the samples of high school seniors and in the multiple-year longitudinal sample but not in the samples of second year undergraduates. That is, even when controlling for ability, interest, investment, and other relevant variables, self-rated STEM ability remained a significant predictor of persistence for the sample of high school seniors interested in STEM and for the multiple-year longitudinal sample. Because the self-rated ability measure was completed when students were high school seniors, it may not have predicted persistence in the sample of second year undergraduates due to the amount of time that passed between its measurement and the measurement of STEM persistence. Due to changes in self-rated ability during college (e.g., Sax, 2008), a later measurement of self-rated STEM ability (e.g., during the second year of college) may have been a better predictor of persistence during the later years of college. Some researchers have concluded that self-efficacy is the most important predictor of achievement and persistence in a field (e.g., Vogt, Hocevar, & Hagedorn, 2007). For example, Hackett (1985) noted:

> At least with college-aged women and men, self-efficacy expectations with regard to occupations and career-related domains are much more important than

> measured ability. Self-efficacy expectations encompass ability information but are significantly more predictive of career choice behavior than ability or performance. (p. 55)

In the present study's samples of high school seniors and in the multiple-year longitudinal sample, math ability (as measured by SAT-Math) was a better predictor of persistence than was self-rated STEM ability. In the samples of second year undergraduates and in the multiple-year longitudinal sample, performance (as measured by undergraduate STEM GPA) was a much better predictor of persistence than was self-rated STEM ability. Thus, although the present research identified self-rated STEM ability as an important predictor of persistence for some samples, it did not support the assertion that self-efficacy is more important than measured ability in regards to undergraduate major selection and persistence.

Relative non-STEM ability and achievement. Although the use of measures of non-STEM ability and achievement to predict STEM persistence is not very common, I included such measures of tilt in the present study to explore whether abilities and achievement in non-STEM domains may draw students away from STEM majors. Bivariate results were consistent with the prediction that relative non-STEM ability and achievement would be negatively related to persistence. In all samples, bivariate analyses indicated that those who did not persist in STEM had higher relative non-STEM to STEM strengths than those who did persist. The association between SAT tilt and persistence was weaker in second year samples than in high school samples, which may reflect both the differences in time between predictor and criterion measurements for the two samples as well as the more restricted group of second year STEM majors (compared to the more variable group of high school seniors interested in STEM). The association between undergraduate GPA tilt and STEM persistence was stronger in second year samples than in high school samples, which may be partially due to the fact that the undergraduate GPAs for the second year samples reflected a longer time period and more course grades than for the high school sample.

In multivariate models that included all predictors, SAT tilt had a significant negative coefficient in all samples except for the biological science samples, indicating that net of other relevant predictors, higher SAT tilt toward verbal ability was associated with decreased persistence in STEM. This is consistent with the idea that high relative non-STEM ability may discourage persistence in STEM. Students whose verbal ability is high relative to their math ability may feel that their talents are put to better use in non-STEM majors. However, high relative verbal ability did not pull students away from the biological sciences. Perhaps verbal skills are put to use more often in biological science majors than in male-dominated STEM majors.

The multivariate findings for undergraduate GPA tilt did not show the same pattern. Although undergraduate GPA tilt was significant in several multivariate models, it had a positive coefficient, indicating that higher relative non-STEM achievement was associated with increased persistence in STEM. In the multiple-year longitudinal sample, the survival model that included interactions between each variable and time revealed a significant interaction between undergraduate GPA tilt and time; the positive relationship between undergraduate GPA tilt and persistence in STEM was stronger during later years of college than during earlier years of college. Although it is likely that non-STEM college GPA reflects various constructs that are relevant to STEM persistence, such as motivation, good study habits, and cognitive ability, it is not known why earning higher non-STEM relative to STEM grades would be associated with remaining in STEM majors. It may be the case that the size of the correlations among STEM grades, non-STEM grades, and STEM persistence changed the sign of the regression coefficient for undergraduate GPA tilt (e.g., Friedman & Wall, 2005).

High school STEM interest. Interest in STEM majors expressed during high school was expected to be an important predictor of persistence in STEM, and bivariate analyses were generally consistent with this hypothesis. In all samples except for the sample of high school seniors interested in biological science majors (where interest had a near-zero relationship with persistence), those who persisted in STEM had indicated higher STEM interest in high school than those who did not persist in STEM. The relationship between high school STEM interest and persistence was weakest in the biological science samples.

Similarly, multivariate analyses indicated that high school interest in STEM was a significant predictor of persistence in male-dominated STEM samples (and in overall second year and multiple-year longitudinal samples), but not in biological science samples. It is not clear why interest would be more important to STEM persistence for male-dominated STEM majors than for biological science majors. Perhaps many students who choose biological science majors have a history of a wider variety of interests that include both STEM and non-STEM interests, whereas those choosing male-dominated

STEM majors have longer term interests that are more focused in STEM. Many students planning to enter medical professions may select health-related majors (not classified as STEM in the current study) as their intended majors during high school but may eventually select a biological science major during college (e.g., a student whose college does not have a formal pre-medical major may decide to earn an undergraduate degree in biology before attending medical school), weakening the relationship between STEM interest and persistence for biological science samples.

High school extracurricular activities, awards, and officer positions in STEM. As another indicator of interest and investment, participation in science, math, and computer extracurricular activities (including holding an officer position or earning an award in these activities) was expected to be positively associated with STEM persistence. Bivariate analyses generally supported this prediction. In all samples except for the second year biological science sample, those who persisted in STEM had higher participation in extracurricular STEM activities than those who did not persist. Extracurricular STEM activity participation differences between those persisting in and those leaving STEM were larger in the samples of high school seniors than in the samples of second year undergraduates. Because extracurricular activity participation was measured during high school, it was a more proximal measure of STEM investment and interest for the high school sample than for the second year undergraduate sample.

In multivariate analyses for the samples of high school seniors and the multiple-year longitudinal sample, the extracurricular activities and awards in STEM variable was a significant positive predictor of persistence. On the other hand, in the overall sample of second year undergraduates and in the prediction of persistence in male-dominated STEM fields for second year undergraduates, the extracurricular activities and awards in STEM variable was a significant negative predictor of persistence in the models including all predictors. It is not clear why higher participation in extracurricular activities in STEM during high school would be associated with lower STEM persistence rates from the second to fourth year of college. However, when undergraduate GPAs were excluded as predictors, the negative effect for extracurricular activities and awards in the second year samples was no longer significant.

Degree goal. Because degree goal was expected to be associated with motivation and commitment, it was also expected to predict STEM persistence. Bivariate analyses in most samples were consistent with this prediction, as those who intended to earn graduate degrees were more likely to persist in STEM than those who intended to earn bachelor's degrees. The one exception was in the sample of high school seniors interested in male-dominated STEM fields, where those intending to earn graduate degrees were equally likely as those intending to earn bachelor's degrees to persist in male-dominated STEM majors.

In multivariate analyses, the effects of degree goal were inconsistent across samples. In the high school biological science sample and the multiple-year longitudinal sample, aspiring to a graduate degree was positively associated with persistence in STEM. In the high school male-dominated STEM sample, having a degree goal of graduate degree was negatively associated with persisting in STEM and male-dominated STEM majors. The degree goal coefficient was not significant in the remaining samples.

Thus, although bivariate analyses were generally consistent with previous research indicating that higher degree goals predict persistence in STEM during college (Chen & Weko, 2009; Huang et al., 2000), I found that after considering other relevant predictors, degree goal often had either an opposite effect or else no significant effect. Degree goal may not have been a significant predictor because its associated features, such as motivation and commitment, are likely reflected in other predictors as well (e.g., undergraduate STEM GPA). It is also the case that a student could fail to persist in STEM but retain his/her degree goal by pursuing non-STEM graduate studies.

SES. Because SES has been found to be positively associated with persistence in STEM (e.g., Baum et al., 2010; Gayles & Ampaw, 2011), it was expected to be a predictor of STEM persistence. Although bivariate analyses supported this prediction, and those who persisted in STEM were, on average, from higher SES families than those who did not persist, effects were often small. Furthermore, SES was not significant in the majority of multivariate models. The effects of SES may impact persistence through other relevant predictors of persistence such as academic preparation, but direct effects disappeared in multivariate models. To summarize, even though bivariate effects for SES were found, these effects generally became nonsignificant when other relevant predictors were considered.

Race/ethnicity. Based on prior research, it was expected that Asian students would have higher persistence rates than students in any other racial/ethnic group and that White students would have higher persistence rates than Black and Hispanic students. Bivariate results in the present study tended to support these predictions; in all but the second year male-dominated STEM sample, Asian students were more likely to persist than students of any other race/ethnicity, followed by White students. In the samples of high school students, Asians persisted at nearly twice the rate of other racial/ethnic minorities. Racial/ethnic differences were smaller in the sample of second year undergraduates, with the persistence rate of Asian students being only slightly larger than that of other racial/ethnic groups. White students' persistence rates typically differed only slightly from Hispanic and Black students' persistence rates.

Multivariate results were mixed across the samples. In the high school overall STEM sample and male-dominated STEM sample, there were significant positive race/ethnicity coefficients indicating that Black, Hispanic, and Asian students were all more likely than White students to persist. In the high school biological science sample and multiple-year longitudinal sample, these results, minus the significant Hispanic coefficient, were also found. Similarly, Tyson et al. (2007) found that even though Hispanic and Black high school graduates were less likely than Whites to earn a college degree, among those who did earn college degrees, Hispanics and Blacks were just as likely as Whites to earn their degree in a STEM field; in fact, after controlling for high school math and science course taking, Hispanic students were significantly more likely than White students to earn their degree in a STEM field. However, these results were not supported by findings from the samples of second year undergraduates. In the sample of second year undergraduates interested in any STEM field, the only significant race/ethnicity coefficient in a multivariate model was the Hispanic-White comparison in the model excluding college GPAs; the coefficient was negative, indicating Hispanic students were less likely than White students to persist. Because race/ethnicity (Hispanic-White) predicted undergraduate STEM GPA and because the effect of race/ethnicity on persistence became nonsignificant when undergraduate STEM GPA was added as a predictor, the relationship between race/ethnicity (Hispanic-White) and persistence was mediated by undergraduate STEM GPA. In the sample of second year undergraduates with male-dominated STEM majors, the coefficient for the Asian-White comparison was significant but negative, indicating Asian students were less likely than White students to persist in male-dominated STEM fields. Thus, there was no consistent pattern of multivariate results for race/ethnicity across the samples. Net of other predictors, Whites may be less likely than other racial/ethnic groups to persist in STEM during the early years of college but equally or more likely to persist during the final years of college.

Gender. Although the present study included a variety of variables that were expected to help explain why females leave STEM majors at higher rates than males, gender effects remained significant in the models including all individual-level predictors, with the exception of the second year biological science sample. Given that women fared worse than men on many of these predictors that were related to persistence in STEM, it would be reasonable to expect the gender effect to disappear when considering all of these predictors simultaneously (i.e., in multivariate analyses). However, even when accounting for other relevant predictors, gender remained significant in most multivariate analyses. Nevertheless, in most samples, individual-level models led to a reduction in gender effects. That is, the male-to-female odds ratios for persistence were reduced when other relevant individual-level predictors were added to the models (see Table 91). This was expected, considering that the largest male advantage was found for variables that were some of the best predictors of persistence. For example, in the high school sample, males earned higher SAT-Math scores, had stronger relative math to verbal ability, had taken more STEM coursework in high school, had participated in more STEM extracurricular activities, and had higher self-rated STEM ability than females, all of which were significantly associated with higher STEM persistence rates. Therefore, these predictors can be used to explain some portion of the gender differences in STEM persistence. However, females outscored males on some important predictors of persistence (e.g., high school achievement, undergraduate STEM GPA in several samples), so including these predictors did not help to explain why females were less likely than males to persist in STEM.

Reductions in gender effects (i.e., the decrease in male-to-female odds ratios for STEM persistence) were greater for the high school senior samples than for the second year undergraduate samples. That is, the additional predictors accounted for a larger portion of the gender effect in the high school senior samples than in the second year undergraduate samples. This may be in part due to the finding that the predictors measured during high school were often better predictors in the high school samples, perhaps because more time had passed between predictor and outcome measurement for the second year undergraduate samples. Gender differences in persistence were also larger to begin with for the high school samples than for the second year undergraduate samples.

Summary of individual-level predictors of STEM persistence. Bivariate predictions were generally supported. Those who persisted in STEM majors tended to have higher values than those who did not persist for SAT-Math, high school achievement, high school STEM coursework, high school extracurricular activities and awards in STEM, self-rated ability in STEM, high school interest in STEM, undergraduate STEM grades, degree goal, and SES. Negatively associated with persistence in bivariate analyses were SAT tilt and undergraduate GPA tilt, as predicted. Asian students tended to have the highest persistence rates of any race/ethnicity, and males typically had higher persistence rates than females. Bivariate effects for some variables (e.g., SAT-Math, SAT tilt, high school STEM coursework, extracurricular activities and awards in STEM, self-rated STEM ability) were larger in the sample of high school seniors than in the sample of second year undergraduates. This effect was hypothesized to be caused by multiple factors, including (a) different time lags between the measurement of predictors and criterion across samples, as two years passed between the measurement of most predictors and the measurement of STEM persistence for the high school sample, whereas four years passed between these measurements for the second year undergraduate sample; and (b) increased attrition in the second year undergraduate sample, which led to the sample being more restricted on several characteristics compared to the high school sample. Some variables (e.g., SAT-Math, SAT tilt, high school achievement, high school STEM coursework, self-rated STEM ability, high school STEM interest) were better bivariate predictors in male-dominated STEM samples than in biological science samples. This may be due to differing types of coursework and abilities required for biological science majors compared to other STEM majors.

Predictors identified in multivariate analyses as independent contributors to persistence varied somewhat across the samples, but several patterns emerged. Undergraduate GPA in STEM was one of the best predictors of persistence in the samples of second year undergraduates and in the multiple-year longitudinal sample. SAT-Math was one of the best predictors of persistence in all high school samples but had an indirect effect on persistence (mediated by undergraduate STEM GPA) in second year samples. Similarly, high school achievement had either a significant direct or indirect effect on persistence in all samples. Additionally, gender remained significant in most samples, indicating that females were less likely than males to persist in STEM, even after accounting for a wide variety of relevant predictors. Across all samples, ability and achievement were critical in predicting STEM persistence, even when controlling for many other factors.

Differences between the samples of high school seniors and the samples of second year undergraduates were observed. High school coursework in STEM and self-rated STEM ability were significant predictors in the samples of high school seniors but did not have significant direct effects in the second year samples. High school extracurricular activities and awards in STEM were positively associated with persistence in the high school samples but negatively associated with persistence or not significant in the second year samples. SAT-Math and high school achievement tended to have direct effects on persistence in STEM through the second year of college but indirect effects on persistence in STEM through the fourth year of college. Whereas high school STEM coursework, self-rated STEM ability, extracurricular activities and awards in STEM, SAT-Math, and high school achievement were stronger predictors of STEM persistence in the high school samples than in the second year undergraduate samples, undergraduate STEM GPA was a better predictor in the second year undergraduate samples than in the high school samples. Comparison of regression models for the male-dominated STEM and biological science samples indicates that SAT tilt and high school STEM interest were significant predictors only in the male-dominated STEM samples.

Overall, the most important predictors of persistence in the samples of high school seniors were gender and SAT-Math, whereas the most important predictor in the samples of second year college students was undergraduate STEM GPA. Predictions made in Hypothesis 26 about important predictors in multivariate models were all at least partially supported. As predicted, SAT-Math and high school achievement were significant predictors in all samples, either direct or indirectly influencing persistence in STEM. Predictions about the importance of undergraduate STEM GPA, interest, and gender in multivariate models were supported in most but not all samples.

School-level Predictors of Persistence in STEM Majors

Because of the expected importance of environmental features on students' persistence in STEM majors, I examined several school-level predictors in the present study. It was predicted that undergraduate females' proportional representation in STEM majors at colleges would predict their persistence, such that a larger female undergraduate representation in STEM would be associated with increased STEM persistence for females at that college (Hypothesis 24), but this received limited support in the present study. It was also expected that students at private colleges would have higher persistence rates than those at public colleges (Hypothesis 25), but this prediction was not supported. No predictions were made about the effects that a college's undergraduate admission rate or a college cohort's SAT scores would have on STEM persistence; although bivariate effects in some samples indicated that cohort SAT predicted STEM persistence, it was not significant in the majority of multivariate analyses. Each of these school-level predictors is discussed below.

Undergraduate females' proportional representation in STEM. Due to previous findings on the effects of females' proportional representation on women's performance and retention (e.g., Kanter, 1977), females' representation in STEM at colleges was expected to affect their persistence in STEM. Although the interaction between individual gender and the proportion of a school's STEM undergraduates who were female was significant in multivariate analyses for several samples, the form of the interaction was not always consistent with expectations. In the sample of high school students interested in STEM, the interaction was ordinal; males were more likely to persist for all values of female STEM representation, but the difference was smallest when female representation in STEM at a college was high. However, both males and females became less likely to persist as female representation increased. For the high school biological science sample, the interaction between gender and female STEM representation was consistent with expectations. Males' persistence rates were similar regardless of the proportion of females in STEM, whereas females were more likely to persist when female representation in STEM was high than when it was low.

In the sample of second year undergraduates, the interaction was similar to the one found for the sample of high school students interested in STEM in that both males and females were less likely to persist when female representation in STEM was high. However, in the second year sample, the interaction was disordinal; whereas males were more likely than females to persist when female representation in STEM was low, females were more likely than males to persist when female representation in STEM was high. A similar finding emerged for the sample of second year male-dominated STEM majors, though the effect for males was stronger in this sample; the difference between males' and females' persistence rates at schools with high female representation in STEM was larger in the male-dominated STEM sample than in the overall second year sample. The interaction between gender and female STEM representation was significant in the multiple-year longitudinal sample, but it took yet another form. In this case, females' persistence rates were quite consistent across levels of female STEM representation, whereas males became less likely to persist as female STEM representation increased.

It was not clear why persistence was often lower for both genders when female STEM representation was high compared to when it was low or why the influence of female STEM representation tended to be stronger for males than females (i.e., the slopes for males were steeper, with the exception of the high school biological science sample). In an attempt to further explain these puzzling findings regarding the interaction between gender and female representation in STEM, all multilevel models were re-run to include school-level STEM persistence rate as a predictor. After accounting for a college's STEM persistence rate, the previously significant interaction between female representation in STEM and gender was no longer significant in the second year undergraduate samples but was significant in the samples of high school seniors interested in STEM and male-dominated STEM majors (see Appendix B). The form of the interaction in the overall high school sample remained the same when school-level persistence was included as a predictor, with both males and females becoming less likely to persist as the proportion of females in STEM increased (see Figure B1). In the sample of high school students interested in male-dominated STEM fields, the interaction between gender and female STEM representation was not significant in the original model, but it became significant when school-level persistence rate was added as a predictor. In this sample, after accounting for a school's STEM persistence rate, females became slightly more likely to persist in STEM as their STEM representation at a college increased, and males became slightly less likely to persist as female STEM representation increased (see Figure B2). This interaction is consistent with the idea that females' persistence rates are increased when they are surrounded by more females in STEM. However, inconsistent effects across samples temper conclusions that can be drawn about the influence of females' proportional representation in STEM on persistence in STEM.

Although the present study used a measure of females' proportional representation in undergraduate STEM student bodies, the effects of this variable likely have several explanations. Kanter's (1977) work and follow-up studies (e.g., Kulis et al., 2002) have noted that when women are few in number, others may make more stereotyped decisions, women may have poorly developed professional networks, and the culture likely reflects the majority group. Several researchers have documented the conditions that many women in STEM departments face. Seymour (1995) conducted a three-year longitudinal study with a sample of undergraduates at seven colleges who intended to major in a STEM field at college entry, conducting interviews and focus groups to gain insight into difficulties faced by STEM majors. STEM majors, both male and female, reported that "women were subjected, on a daily basis, to unkind, and sexually suggestive, remarks and jokes intended to make women feel uncomfortable and unwelcome," particularly by male peers (p. 454). Many male participants believed that their female STEM classmates were not as smart as men, and some suggested that women earned good grades in STEM courses by flirting with instructors. Women noted that when their male peers felt threatened by female students' competence, men tried "to devalue them, both as women, and as intellectual competitors" by making inappropriate comments or by attributing women's success to factors not related to ability (p. 456). Female STEM majors reported that their male peers often reacted with anger when females received high grades in STEM courses, leading many of the females to try to hide their good grades from male classmates. Female STEM majors in Seymour's (1995) study also experienced feelings of isolation, with males purposely excluding them from conversations and activities because of their gender; many men agreed that this was true at their colleges. In a smaller-scale study, Wasburn and Miller (2004) conducted a survey with undergraduate women in science, technology, and engineering fields at a single institution about their classroom experiences, finding that many female students felt that men and women were not treated equally by professors in their STEM courses, that women did not feel like equal participants when working in groups with male classmates, and that female students believed faculty needed education about issues concerning female STEM students. In a sample of engineering majors at several colleges, Vogt et al. (2007) found that women reported more discrimination than men, that females believed their male classmates did not respect them as equals, and that females were more likely than males to report having discouraging interactions with professors. It would be no surprise if these types of off-putting experiences drove many women away from STEM majors.

Although these unwelcoming, negative environments in STEM departments are sure to depend on many factors besides women's proportional representation, they may be more likely to occur when female representation is low. When females are greater in number, stereotyped judgments may decrease, and the culture may become less masculine (Kanter, 1977). Additionally, higher female representation may provide females with more opportunities to seek support from other female students. That is, when female STEM students are mistreated because of their gender, having more advanced female student role models may help to prepare incoming female students regarding what to expect, how to handle difficult situations, and where to turn for support (Seymour, 1995). Prior research led to the expectation that women would be more affected by female representation in STEM than would men, but in the present study, men were also influenced by gender representation in STEM. Changes in the environment associated with higher female STEM representation seemed to have a stronger effect on males than on females in many samples. Because the measured variable of female representation in STEM could be associated with various environmental features, it is not clear what exactly is driving this effect. Controlling for a school's overall STEM persistence rate led to the interaction between gender and female STEM representation becoming nonsignificant in many samples, but the inconsistent effect of female STEM representation across samples does not allow for strong conclusions to be made.

Institutional selectivity. Two measures of institutional selectivity were used in the present study: the entering cohort's SAT scores and the proportion of undergraduate applicants who were accepted for admission. Bivariate analyses indicated that in the samples of high school seniors and the multiple-year longitudinal sample, higher cohort SAT scores were associated with increased persistence rates. That is, persistence in STEM was higher at schools where undergraduates were typically higher ability students. This significant correlation was not found in the samples of second year undergraduates. Colleges' undergraduate admission rates were not significantly correlated with persistence in any sample.

Neither of these indicators of institutional selectivity tended to be a significant predictor when included in multivariate models with all available predictors. One exception was the second year biological science sample, where a college's admission rate was negatively associated with persistence. More selective schools (i.e., those admitting smaller proportions of their applicant pool) tended to have higher STEM persistence rates, even when controlling for all other variables. In the multiple-year longitudinal sample, college admission rate was found to interact with time, such that the effect of college admission rate on STEM persistence was stronger during later years of college. As a whole, the findings indicate that more selective colleges may have higher STEM persistence rates, but these effects often disappear when individuals' characteristics are also considered. The bivariate associations may have become nonsignificant in multivariate analyses because of individual-level differences between students at different schools. For example, students at schools with higher cohort SAT scores also had higher SAT scores themselves, and individual-level ability contributed to STEM persistence. In sum, after controlling for available individual-level characteristics of students in the samples, a college's selectivity and cohort ability did not tend to impact students' persistence in STEM.

Public vs. private colleges. Although some prior research has indicated that students at private colleges have higher STEM persistence rates than those at public colleges (e.g., Huang et al., 2000), this was not supported in the present study. No bivariate analyses in any sample indicated that public/private was significantly correlated with persistence in STEM, and public/private was not a significant predictor in any multivariate model predicting STEM persistence. The reported benefits of attending a private school on STEM persistence (e.g., Astin & Astin, 1992), such as smaller class sizes and faculty who focus on high quality teaching, did not matter for STEM persistence in the present samples.

Summary of school-level predictors of STEM persistence. Undergraduate female representation in STEM majors was the only school-level variable that often remained an important predictor of STEM persistence in multivariate models, though its effect varied across samples. STEM persistence during the early years of college was higher at schools with higher ability students, but this effect became nonsignificant after controlling for individual-level student characteristics. In most multivariate models, a college's selectivity, typical undergraduate ability, and whether it was public or private did not tend to significantly affect students' persistence in STEM majors.

Study Limitations and Future Research

The present study had several strengths, including students from many colleges, various relevant predictors at both the individual and college level, and a longitudinal design. Its limitations and how future research may address these are discussed below.

Early STEM-relevant experiences. Data were collected from participants for the first time during their senior year of high school, so prior experiences that shaped high school outcomes are unknown. That is, high school interest in STEM is likely influenced by a variety of previous experiences that were not measured in the present study. Various features of students' school and home lives may be associated with the selection of or persistence in a STEM major. Environmental features that support participation in math and science for middle school, high school, and college students include (a) parents who are involved, provide encouragement, and help with homework; (b) teachers who inspire, give advice on STEM careers, have high expectations, and explain concepts clearly; (c) successful role models with STEM careers; and (d) peers who are interested in math and science, who believe the student is good at math or science, and who support the student's career goals (Fouad, et al., 2010). Maltese and Tai (2011) found that certain teaching techniques in high school math courses (e.g., using hands-on materials) were significant predictors of students' later completion of degrees in STEM fields, even when controlling for achievement and demographic variables. Additionally, students' occupational choices are influenced by their parents' gender role stereotypes and occupational expectations for their children (Chhin, Bleeker, & Jacobs, 2008). The path to a STEM career begins much earlier in life than one's senior year in high school (see also Shaprio & Sax, 2011; Tobias, 1990), so longitudinal studies that begin to measure relevant variables prior to high school could shed additional light on why people choose to enter and persist in the STEM pipeline.

Measuring these early factors that are relevant to STEM persistence may also help to further explain gender differences in STEM entry and persistence. For example, Kahle, Parker, Rennie, and Riley (1993) found that elementary school teachers believed that confidence, interest, and performance in science were higher for male students than for female students. Furthermore, in behavioral observations, Kahle et al. noted that some teachers were more likely to initiate interactions with males than females and to allow males to dominate discussions and resources during science classes. Early classroom experiences such as these affect persistence in math and science (Fouad, et al., 2010), so some gender difference may stem from these experiences. More research on early experiences that discourage females from liking or pursuing science and math could also help to explain females' current underrepresentation in STEM careers. Leslie et al. (1998) note:

> One cannot understand why women…are underrepresented in science and engineering unless one understands that the related behaviors are formed over at least half a lifetime, but especially in the years prior to college. Although collegiate interventions no doubt can increase female…participation rates, the critical damage is done much earlier. (p. 268)

Additionally, some interesting changes in females' and males' math and science ability, achievement, and attitudes have been documented. During elementary school, girls' and boys' math and science ability and achievement test scores are similar, but starting in middle school and continuing into high school and beyond, boys tend to score higher than girls (Xie & Shauman, 2003). Similarly, boys and girls have equally positive attitudes toward math and science during elementary school, but after they reach middle school, boys' attitudes toward math and science are more positive than girls', and these gender differences become larger during high school (see Astin & Sax, 1996). Research that provides new insights into why these changes occur could be very useful in regards to understanding gender representation in the STEM pipeline.

Additional individual characteristics. There are other relevant predictors of persistence that could have been measured during high school or college but were not available to be used in the present study. Because I used an existing dataset, I could not choose to include additional individual-level variables that had not already been measured. Although many individual-level variables were included in present analyses, others could have helped to improve prediction, particularly those collected during college, as a majority of the predictors in the present study were collected during high school. College activities such as participating in research, working as a teaching assistant, talking to faculty outside of class, and tutoring other students are related to persistence in STEM during college (Astin & Sax, 1996; President's Council of Advisors on Science and Technology, 2012). Similarly, Gayles and Ampaw (2011) found that social integration during college, which included activities such as participation in clubs and activities, predicted earning a STEM degree in a sample of students who had declared STEM degrees earlier in college. In a qualitative study with a small sample of women engineers, Tharp (2002) summarized external supports to continuing in the field, including economic factors (e.g., financial assistance for schooling), having a family member who was an engineer, systemic support (e.g., summer institutes providing information about engineering careers), family support and values, encouragement from teachers and counselors, having role models and mentors, and getting personal and professional peer support. Personal circumstances of the participants were also unknown in the present study, and some life choices (e.g., having a child) are associated with an increased probability of earning a non-STEM rather than a STEM degree (Maltese & Tai, 2011). From a young age, females are more likely than males to be willing to make career sacrifices for their families and may leave STEM fields due to work-family balance issues (see Frome, Alfeld, Eccles, & Barber, 2008). Examining students' personal goals and situations as well as their involvement in various college experiences could help to improve prediction of STEM persistence as well as help to explain some portion of gender differences in STEM persistence.

Additional environmental predictors. Results of the present study could lead to the conclusion that individuals' characteristics are much more important than environmental features in determining STEM persistence. Although this could be true, the college-level variables available in the present study were somewhat limited. Other environmental variables could have potentially helped to explain why females have lower STEM persistence rates than males, even after accounting for a variety of relevant variables. Although I used females' proportional representation in STEM as a proxy for the STEM environment at a college, more direct measures of this environment would have been helpful, such as measures of (a) unwelcoming attitudes toward or treatment of women (e.g., the "chilly climate hypothesis"; see Strenta et al., 1994); (b) the representation of women in STEM faculty, as a male-dominated faculty may affect the culture of the department and leave female students with few same-sex role models; and (c) the frequency of discriminatory behaviors that may leave women feeling frustrated and alienated (Seymour, 1995).

Much attention has been paid to the culture in STEM departments, including the previously discussed negative treatment of women, the focus on competition between students, the difficulty and pace of coursework, and the lecture format of many classes. Vogt et al. (2007) described majoring in STEM as:

> male-normed…competitive, weed-out systems that are hierarchically structured with impersonal professors. These characteristics are acknowledged as customary, even respectable, teaching practices in traditional research university science, mathematics, and engineering classrooms. It is also these classrooms that have

> caused self-doubt in women, perhaps resulting in their attrition from science, mathematics, and engineering. (p. 339)

Compared to faculty in non-STEM fields, faculty in STEM fields have been found to be more likely to depend on lecturing during class rather than on classroom discussions, to grade on a curve, to hire graduate assistants to teach courses, to report a stronger preference for research over teaching, and to believe that the quality of their undergraduate students is poor (Astin & Astin, 1992). In a unique study, Tobias (1990) recruited a small group of college graduates who had never taken science courses in college (but had taken four years of high school math) and asked them to "seriously audit" an introductory course in calculus-based physics or chemistry and to focus on features that may lead students to see the course as difficult or alienating. Participants noted that the "sense of competition" in the courses "precludes any desire to work with or to help other people….Suddenly your classmates are your enemies" (p. 18). Participants also stated that the pace of the science courses was much faster and required more work outside of class than they were accustomed to in their other non-STEM majors and that impersonal, lecture-based classes provided few opportunities for student interaction or involvement. They did not see the lectures as stimulating or interesting. Even a professor teaching one of the courses noted, "It is dull. It is dull to learn, and it is dull to teach. Unfortunately, it is the basic nuts and bolts stuff that must be mastered before anything useful can be accomplished" (p. 24). These features of STEM faculty and courses have been hypothesized to drive students, particularly female students, away from STEM majors.

Some researchers have focused specifically on the competitive nature of college STEM courses in making STEM less appealing to women than to men. For example, undergraduate men are much more likely than women to describe themselves as competitive (Sax, 2008), and in a sample of engineering majors at four selective colleges, Strenta et al. (1994) found that women were more likely than men to view introductory courses in the major as too competitive. Males also may be more likely than females to improve their performance in competitive environments, leading to increased success and persistence for males. Gneezy, Niederle, and Rustichini (2003) found that whereas men significantly increased their performance on a problem solving task in competitive environments (compared to their performance in non-competitive environments), women had similar performance across environments, leading to a significant male advantage in performance only in competitive environments. When controlling for ability, women underperformed in competitive environments. Interestingly, Gneezy et al. (2003) also found that in competitive environments, women performed worse when competing against men than when competing against other women. The authors attributed their findings partially to women's feelings of lowered competence when comparing themselves to men. Although not available in the present study, additional information about college STEM departments' cultures, such as teaching strategies, grading policies, and competitiveness, may help to explain STEM persistence as well as gender differences in STEM persistence.

Decisions made by others. In the present study, it is unknown whether students themselves decided to leave STEM majors or whether they were forced to choose other majors based on decisions made by others (e.g., they were not accepted into the STEM majors they desired). Gender discrimination may have directly affected (e.g., via decisions that impeded persistence) or indirectly affected (e.g., through its impact on grades or on opportunities available to females to enhance their STEM education) females' persistence. In an experimental study, Moss-Racusin, Dovidio, Brescoll, Graham, and Handelsman (2012) asked biology, chemistry, and physics professors from various research universities to rate the application materials of a student who was applying for a laboratory manager position, with the application materials being randomly assigned a male or a female name. Faculty participants who believed the applicant was male rated the applicant as significantly more hireable, offered a higher starting salary, believed the applicant was more competent, and offered more career mentoring than those who believed the applicant was female. Bias did not differ by faculty participant discipline, gender, tenure, or age. Though the presence and magnitude of gender bias may be difficult to measure outside of experimental studies, some research suggests that gender bias may play a role in females' underrepresentation in the STEM pipeline.

Some researchers point to masculine stereotypes of many STEM fields as being responsible for gender bias. Even though typical gender roles have changed over time (e.g., increased female participation in the labor force and in particular occupations; Pettit & Hook, 2009), people's views of how women are and should be have not necessarily changed much (e.g., Lueptow, Garovich, & Lueptow, 1995). Males are more likely than females to be seen as competitive, decisive, and self-confident (Lueptow et al., 1995), which may affect the extent to which individual males and females are seen as compatible with traditionally masculine fields such as the hard sciences. The impact of gender stereotypes and discrimination on females' persistence in male-dominated STEM majors and careers are interesting topics for future study.

Post-college persistence in STEM. Finally, because the variables in the present sample were measured during high school and college, it is unknown whether the participants pursued careers in STEM fields after college. The strong focus of many organizations and government agencies is "fostering a pipeline of future STEM professionals" (Office of the Director of National Intelligence, 2011, p. 7), so although earning a STEM degree may be an important step in becoming a STEM professional, it is often not the primary outcome of interest. It is certainly the case that some students who earn degrees in STEM fields pursue jobs or careers in non-STEM fields. For instance, in a sample of several hundred high ability students who entered college with STEM majors, Seymour (2001) found that among those who persisted in STEM through college graduation, nearly 17 percent intended to pursue work in a non-STEM field following graduation. In a large, national sample of college graduates in a wide age range (22 to 75 years old) who had earned a bachelor's degree in a STEM field, Graham and Smith (2005) found that 53 percent of women and 40 percent of men were employed in a non-STEM field. However, graduates with degrees in engineering and computer science are more likely to work in congruent jobs than are graduates with many other degrees (Robst, 2007). Even so, at least some students in the present samples are likely to leave the STEM pipeline at some point after college.

An undergraduate STEM degree is also an important prerequisite for graduate studies in STEM, and a graduate degree in STEM is projected to be required for 28 percent of new job openings in STEM fields (President's Council of Advisors on Science and Technology, 2012). In a large, national sample of graduating college students, Astin and Astin (1992) found that among those who planned to attend graduate school in STEM fields, the majority had also majored in a STEM field as an undergraduate. For those planning to attend graduate school in a biological or physical science field, more than 80 percent had an undergraduate degree in a biological science, physical science, or engineering field, and for those planning to attend graduate school in an engineering field, more than 90 percent had an undergraduate degree in a biological science, physical science, or engineering field. It seems likely that most students with undergraduate degrees in non-STEM fields would not have the preparation (e.g., appropriate course taking) required to begin graduate study in a STEM field. The path to a STEM career is often preceded by an undergraduate degree in STEM, and the present study identified factors that affect the loss of students from the STEM pipeline during their undergraduate education, which may prevent them from pursuing a graduate degree in STEM or a STEM career. Research that follows students for longer periods (e.g., from high school through post-college) to assess the effects of different variables on persistence in the STEM pipeline at different times would certainly be fruitful.

Conclusion

In summary, the present study examined how a variety of variables affected persistence in STEM fields during college. Individual-level predictors with the largest effects in multivariate analyses included SAT-Math for high school seniors interested in STEM and undergraduate STEM GPA for samples of second year undergraduate STEM majors and for the multiple-year longitudinal sample. SAT-Math and high school achievement had direct or indirect effects in all samples. Additionally, high school STEM interest, extracurricular activities and awards in STEM, SAT tilt, high school STEM coursework, and self-rated STEM ability were significant predictors in many samples.

To the extent that any of these predictors can be targeted in interventions, STEM persistence may increase. Although the goal of recruiting students into STEM is not uncommon, it is prudent to pay attention to the characteristics of students who are being recruited. It would help those designing interventions aimed at encouraging students to choose STEM majors to be aware of individual characteristics associated with persistence among those who choose STEM majors. Similarly, support programs designed to encourage students to remain in STEM majors could focus on the features most strongly associated with persistence. For example, because students who lack the ability to perform well in their college STEM courses are likely to leave STEM majors, high ability, high achieving students could be identified as good candidates to encourage to pursue STEM majors due to their higher likelihood of future success and persistence. Programs designed to encourage students to enter or remain in STEM should consider the importance of not only interest but prior preparation and achievement in STEM. If students are persuaded to select STEM majors but do not have the appropriate prior training or skills, their probability of success and persistence will likely be low. Interventions designed to address entering college students' lack of preparation in math, such as improving teaching methods of high school math teachers, implementing remedial math programs, providing one-on-one math tutoring, and encouraging students to continue taking math classes through their senior year of high school (see President's Council of Advisors on Science and Technology, 2012) may be particularly helpful in leaving the door open for more students to choose STEM majors in college. Achievement, ability, interest, and preparation in STEM are critical factors in students' persistence in STEM majors during college, so programs that target multiple predictors may be more likely to have successful results. For example, out-of-school STEM programs that provide elementary and high school students with opportunities to work with mentors on challenging, hands-on science projects that align with school curriculum (see Office of the Director of National Intelligence, 2011 for examples) may lead to improved STEM-related skills, achievement, and interest. Coordination of multiple extracurricular interventions that aim to develop students' STEM-related interests, achievement, abilities, and self-confidence over time may be particularly likely to succeed in helping students to enter and remain in STEM fields.

One college-level variable in the present study was identified as being potentially important for persistence, particularly in dealing with females' low representation and persistence in most STEM fields. The proportional representation of females in undergraduate STEM majors was generally found to affect persistence in STEM. However, effects varied across samples, and more research is needed to understand environments that may be more or less conducive to females' pursuit of STEM degrees. In the present study, even when controlling for various relevant predictors, gender effects typically remained significant and often were quite large. This finding highlights the need for additional research on college environments and experiences that cause women to leave STEM majors at significantly higher rates than men. Given the increasing need for STEM professionals and women's low entry rates into STEM fields, finding ways to encourage persistence among the relatively small number of women who choose to enter STEM majors seems a worthwhile endeavor. As Astin and Sax (1996) noted:

> Higher education cannot reverse the influence of years of socialization on women's career decisions, so the challenge is to maintain the aspirations of the tiny percentage who have not already turned away, while keeping the door open for women who rediscover science during college. (p. 96)

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Table 1

Summary of Predictors and Hypotheses

Predictor	Gender Hypothesized to Score Higher	Hypothesized Direction of Relationship with STEM Persistence
Individual-level Predictors		
SAT-Math	Males (H2)	Positive (H3)
High school achievement	Females (H4)	Positive (H6)
Undergraduate STEM GPA	None	Positive (H7)
High school STEM coursework	Males (H8)	Positive (H9)
Self-rated STEM ability	Males (H10)	Positive (H11)
High school interest in STEM	Males (H12)	Positive (H14)
High school extracurricular activities and awards in STEM	Males (H13)	Positive (H15)
SAT tilt[a]	Females (H16)	Negative (H18)
Undergraduate GPA tilt[b]	Females (H17)	Negative (H19)
Degree goal	Males (H20)	Positive (H21)
SES	None	Positive (H22)
Race/ethnicity	None	Asian students will have the highest persistence rates; White students will have higher persistence rates than Black and Hispanic students (H23)
Gender	NA	Males will have higher persistence rates than females (H1)
School-level Predictors		
Proportion females in STEM[c]	None	Females' persistence rates will increase as their proportional representation increases (H24)
Public/Private	None	Private colleges will have higher persistence rates than public colleges (H25)
Cohort SAT[d]	None	None
Admission rate[e]	None	None

Note. None = no prediction made. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [c]proportion of undergraduate STEM students at the school who are female. [d]25th percentile SAT score of entering cohort of undergraduates. [e]proportion of undergraduate applicants admitted to the school.

Table 2

Persistence by STEM Subfield in Sample of High School Seniors Interested in STEM Fields

Major Choice during High School	Second Year Major: Biological Sciences	Physical Sciences	Math	Computer Sciences	Engineering	Non-STEM	Total
Biological sciences	2,688 (.36)	340 (.05)	59 (.01)	48 (.01)	588 (.08)	3,684 (.50)	7,407
Physical sciences	528 (.05)	337 (.03)	91 (.01)	103 (.01)	543 (.05)	8,411 (.84)	10,013
Math	31 (.06)	25 (.05)	89 (.18)	17 (.03)	142 (.28)	201 (.40)	505
Computer sciences	173 (.03)	158 (.03)	99 (.02)	1,505 (.28)	1,337 (.25)	2,098 (.39)	5,370
Engineering	509 (.04)	244 (.02)	341 (.03)	184 (.01)	2,350 (.18)	9,739 (.73)	13,367
Non-STEM	2,903 (.13)	667 (.03)	364 (.02)	785 (.03)	2,128 (.09)	16,200 (.70)	23,047
Total	3,652	975	594	1,714	4,382	22,567	

Note. Cells contain counts followed by row-wise proportions in parentheses. Row-wise proportions may not total 1.0 due to rounding. Participants could choose multiple majors during high school.

Table 3

Persistence by STEM Subfield and Gender in Sample of High School Seniors Interested in STEM Fields

Major Choice during High School	Second Year Major: Biological Sciences	Physical Sciences	Math	Computer Sciences	Engineering	Non-STEM	Total
				Males			
Biological sciences	979 (.36)	161 (.06)	31 (.01)	34 (.01)	365 (.13)	1,144 (.42)	2,714
Physical sciences	237 (.05)	211 (.04)	51 (.01)	88 (.02)	400 (.08)	3,758 (.79)	4,745
Math	11 (.04)	16 (.05)	50 (.16)	16 (.05)	110 (.35)	108 (.35)	311
Computer sciences	134 (.03)	141 (.03)	78 (.02)	1,369 (.30)	1,230 (.27)	1,646 (.36)	4,598
Engineering	203 (.04)	129 (.03)	126 (.03)	150 (.03)	1,886 (.38)	2,534 (.50)	5,028
Non-STEM	1,110 (.11)	364 (.04)	179 (.02)	672 (.07)	1,626 (.16)	6,255 (.61)	10,206
Total	1,433	576	285	1,530	3,537	8,469	
				Females			
Biological sciences	1,709 (.36)	179 (.04)	28 (.01)	14 (.00)	223 (.05)	2,540 (.54)	4,693
Physical sciences	291 (.06)	126 (.02)	40 (.01)	15 (.00)	143 (.03)	4,653 (.88)	5,268
Math	20 (.10)	9 (.05)	39 (.20)	1 (.01)	32 (.16)	93 (.48)	194
Computer sciences	39 (.05)	17 (.02)	21 (.03)	136 (.18)	107 (.14)	452 (.59)	772
Engineering	306 (.04)	115 (.01)	215 (.03)	34 (.00)	464 (.06)	7,205 (.86)	8,339
Non-STEM	1,793 (.14)	303 (.02)	185 (.01)	113 (.01)	502 (.04)	9,945 (.77)	12,841
Total	2,219	399	309	184	845	14,098	

Note. Cells contain counts followed by row-wise proportions in parentheses. Row-wise proportions may not total 1.0 due to rounding. Participants could choose multiple majors during high school.

Table 4

Persistence by STEM Subfield in Sample of Second Year Undergraduates Majoring in STEM Fields

	Fourth Year Major						
Second Year Major	Biological Sciences	Physical Sciences	Math	Computer Sciences	Engineering	Non-STEM	Total
Biological sciences	1,219 (.67)	233 (.13)	2 (.00)	4 (.00)	20 (.01)	331 (.18)	1,809
Physical sciences	45 (.09)	292 (.57)	4 (.01)	3 (.01)	74 (.14)	95 (.19)	513
Math	2 (.01)	28 (.10)	132 (.47)	1 (.00)	44 (.16)	74 (.26)	281
Computer sciences	4 (.01)	28 (.06)	3 (.01)	280 (.57)	80 (.16)	100 (.20)	495
Engineering	17 (.01)	23 (.01)	12 (.00)	33 (.01)	2,728 (.88)	280 (.09)	3,093
Total	1,287	604	153	321	2,946	880	6,191

Note. Cells contain counts followed by row-wise proportions in parentheses. Row-wise proportions may not total 1.0 due to rounding.

Table 5

Persistence by STEM Subfield and Gender in Sample of Second Year Undergraduates Majoring in STEM Fields

	Fourth Year Major						
Second Year Major	Biological Sciences	Physical Sciences	Math	Computer Sciences	Engineering	Non-STEM	Total
				Males			
Biological sciences	497 (.65)	108 (.14)	2 (.00)	4 (.01)	12 (.02)	138 (.18)	761
Physical sciences	22 (.07)	176 (.59)	4 (.01)	3 (.01)	45 (.15)	47 (.16)	297
Math	1 (.01)	15 (.09)	70 (.43)	1 (.01)	28 (.17)	46 (.29)	161
Computer sciences	2 (.00)	24 (.05)	2 (.00)	261 (.57)	73 (.16)	92 (.20)	454
Engineering	9 (.00)	18 (.01)	9 (.00)	29 (.01)	2,205 (.89)	204 (.08)	2,474
Total	531	341	87	298	2,363	527	4,147
				Females			
Biological sciences	722 (.69)	125(.12)	0 (.00)	0 (.00)	8 (.01)	193 (.18)	1,048
Physical sciences	23 (.11)	116 (.54)	0 (.00)	0 (.00)	29 (.13)	48 (.22)	216
Math	1 (.01)	13 (.11)	62 (.52)	0 (.00)	16 (.13)	28 (.23)	120
Computer sciences	2 (.05)	4 (.10)	1 (.02)	19 (.46)	7 (.17)	8 (.20)	41
Engineering	8 (.01)	5 (.01)	3 (.00)	4 (.01)	523 (.84)	76 (.12)	619
Total	756	263	66	23	583	353	2,044

Note. Cells contain counts followed by row-wise proportions in parentheses. Row-wise proportions may not total 1.0 due to rounding.

Table 6

Summary Table: Gender *d*-values and Proportions for All Samples

	HS – STEM	HS – Biological Sciences	HS – Male-dominated STEM	Year 2 – STEM	Year 2 – Biological Sciences	Year 2 – Male-dominated STEM	Multiple-year Longitudinal
	d	*d*	*d*	*d*	*d*	*d*	*d*
SAT-Math	0.57	0.43	0.62	0.40	0.39	0.23	0.43
SAT tilt[a]	-0.38	-0.37	-0.39	-0.42	-0.47	-0.25	-0.45
High school achievement	-0.05	-0.10	-0.01	-0.19	-0.07	-0.26	-0.17
High school STEM coursework	0.18	0.08	0.24	0.04	0.07	-0.02	0.05
High school STEM coursework (excluding biological sciences)			0.27			0.00	
High school extracurricular activities and awards in STEM	0.31	0.16	0.36	0.14	0.11	0.07	0.15
Self-rated STEM ability	0.52	0.39	0.60	0.34	0.35	0.26	0.40
High school interest in STEM	0.09	0.05	0.05	0.37	0.03	0.35	0.28
High school interest in STEM (excluding biological sciences)			0.05			0.44	
Freshman STEM GPA	-0.05	0.01	-0.07				-0.01
Second year STEM GPA							-0.06
Third year STEM GPA				-0.08	0.12	-0.13	-0.09
Freshman GPA tilt[b]	-0.11	-0.15	-0.08				-0.20
Second year GPA tilt[b]							-0.20
Third year GPA tilt[b]				-0.24	-0.34	-0.17	-0.17
SES	0.15	0.16	0.16	0.06	0.20	-0.04	0.10
	Men/ Women	Men/ Women	Men/ Women	Men/ Women	Men/ Women	Men/ Women	Men/ Women
Degree goal							
Graduate degree	.65/.66	.78/.78	.62/.63	.66/.73	.78/.80	.63/.67	.67/.74
Bachelor's degree	.35/.34	.22/.22	.38/.37	.34/.27	.22/.20	.37/.33	.33/.26
Race/ethnicity							
White	.73/.72	.67/.67	.74/.73	.74/.67	.64/.65	.77/.69	.72/.67
Black	.06/.08	.05/.07	.06/.08	.04/.07	.04/.07	.04/.07	.05/.09
Hispanic	09/.09	.07/.09	.09/.10	.06/.05	.07/.06	.05/.05	.08/.08
Asian	.11/.08	.17/.13	.09/.07	.13/.16	.22/.17	.11/.16	.12/.13
Other	.03/.03	.04/.04	.02/.03	.03/.04	.03/.04	.02/.04	.03/.03
Persistence in STEM							
Persisting	.47/.22	.58/.46	.45/.14	.87/.83	.82/.82	.89/.84	.68/.50
Leaving	.53/.78	.42/.54	.55/.86	.13/.17	.18/.18	.11/.16	.65/.45
Persistence in male-dominated STEM							
Persisting			.41/.10			.88/.81	
Leaving			.59/.90			.12/.19	

Note. HS = sample with high school seniors interested in STEM. Year 2 = sample with second year undergraduates choosing a STEM major. Positive *d*s indicate higher scores for males, and negative *d*s indicate higher scores for females. Men/Women = proportion of men/women in each category. [a]SAT-Critical Reading minus SAT-Math. [b]Non-STEM GPA minus STEM GPA.

Table 7

Descriptive Statistics for Predictors by Gender in Sample of High School Seniors Interested in STEM Fields

	Men (*N* = 15,830)		Women (*N* = 18,054)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	617.03	90.14	566.30	89.22	0.57
SAT tilt[a]	-33.42	82.85	-2.69	77.77	-0.38
High school achievement	0.13	0.82	0.17	0.79	-0.05
High school STEM coursework	0.29	0.90	0.14	0.78	0.18
High school extracurricular activities and awards in STEM	0.32	1.16	0.00	0.84	0.31
Self-rated STEM ability	3.34	0.63	2.99	0.67	0.52
High school interest in STEM	4.33	0.98	4.24	1.01	0.09
Freshman STEM GPA	2.88	0.80	2.92	0.81	-0.05
Freshman GPA tilt[b]	0.31	0.67	0.38	0.65	-0.11
SES	0.09	0.81	-0.03	0.84	0.15
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	10,254	.65	11,950	.66	
Bachelor's degree	5,576	.35	6,104	.34	
Race/ethnicity					
White	11,490	.73	12,912	.72	
Black	880	.06	1,422	.08	
Hispanic	1,354	.09	1,687	.09	
Asian	1,682	.11	1,510	.08	
Other	424	.03	523	.03	
Persistence in STEM					
Persisting	7,361	.47	3,956	.22	
Leaving	8,469	.53	14,098	.78	

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA.

Table 8

Descriptive Statistics for Predictors by Gender in Sample of High School Seniors Interested in Biological Science Fields

	Men (N = 2,714)		Women (N = 4,693)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	622.76	86.84	585.20	87.94	0.43
SAT tilt[a]	-30.66	78.09	-2.71	75.60	-0.37
High school achievement	0.29	0.74	0.37	0.68	-0.10
High school STEM coursework	0.46	0.91	0.39	0.84	0.08
High school extracurricular activities and awards in STEM	0.30	1.18	0.13	0.96	0.16
Self-rated STEM ability	3.48	0.56	3.24	0.63	0.39
High school interest in STEM	3.91	1.18	3.85	1.18	0.05
Freshman STEM GPA	2.90	0.77	2.90	0.79	0.01
Freshman GPA tilt[b]	0.39	0.63	0.48	0.63	-0.15
SES	0.19	0.81	0.05	0.84	0.16
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	2,123	.78	3,647	.78	
Bachelor's degree	591	.22	1,046	.22	
Race/ethnicity					
White	1,811	.67	3,147	.67	
Black	143	.05	347	.07	
Hispanic	203	.07	403	.09	
Asian	455	.17	624	.13	
Other	102	.04	172	.04	
Persistence in STEM					
Persisting	1,570	.58	2,153	.46	
Leaving	1,144	.42	2,540	.54	

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA.

Table 9

Descriptive Statistics for Predictors by Gender in Sample of High School Seniors Interested in Male-dominated STEM Fields

	Men (N = 13,503)		Women (N = 13,785)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	616.18	90.73	560.46	88.96	0.62
SAT tilt[a]	-34.17	83.64	-2.60	78.48	-0.39
High school achievement	0.11	0.83	0.11	0.81	-0.01
High school STEM coursework	0.26	0.90	0.06	0.74	0.24
High school STEM coursework (excluding biological sciences)	0.28	0.92	0.05	0.75	0.27
High school extracurricular activities and awards in STEM	0.32	1.17	-0.04	0.79	0.36
Self-rated STEM ability	3.31	0.64	2.92	0.67	0.60
High school interest in STEM	4.42	0.91	4.38	0.90	0.05
High school interest in STEM (excluding biological sciences)	4.41	0.92	4.36	0.92	0.05
Freshman STEM GPA	2.88	0.81	2.93	0.81	-0.07
Freshman GPA tilt[b]	0.30	0.67	0.35	0.66	-0.08
SES	0.08	0.81	-0.06	0.84	0.16
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	8,410	.62	8,619	.63	
Bachelor's degree	5,093	.38	5,166	.37	
Race/ethnicity					
White	9,949	.74	10,067	.73	
Black	763	.06	1,106	.08	
Hispanic	1,180	.09	1,321	.10	
Asian	1,282	.09	927	.07	
Other	329	.02	364	.03	
Persistence in STEM					
Persisting	6,023	.45	1,990	.14	
Leaving	7,480	.55	11,795	.86	
Persistence in male-dominated STEM					
Persisting	5,481	.41	1,369	.10	
Leaving	8,022	.59	12,416	.90	

[a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA.

Table 10

Descriptive Statistics for Predictors by Gender in Sample of Second Year Undergraduates Majoring in STEM Fields

	Men (N = 4,147)		Women (N = 2,044)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	653.46	77.10	621.63	85.79	0.40
SAT tilt[a]	-63.40	78.79	-30.15	77.33	-0.42
High school achievement	0.37	0.70	0.50	0.62	-0.19
High school STEM coursework	0.66	1.07	0.62	0.97	0.04
High school extracurricular activities and awards in STEM	0.45	1.25	0.29	1.13	0.14
Self-rated STEM ability	3.56	0.53	3.37	0.59	0.34
High school interest in STEM	3.22	2.34	2.34	2.41	0.37
Undergraduate STEM GPA	2.97	0.65	3.03	0.65	-0.08
Undergraduate GPA tilt[b]	0.37	0.47	0.48	0.46	-0.24
SES	0.26	0.74	0.22	0.79	0.06
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	2,723	.66	1,497	.73	
Bachelor's degree	1,424	.34	547	.27	
Race/ethnicity					
White	3,082	.74	1,375	.67	
Black	170	.04	139	.07	
Hispanic	230	.06	111	.05	
Asian	556	.13	337	.16	
Other	109	.03	82	.04	
Persistence in STEM					
Persisting	3,620	.87	1,691	.83	
Leaving	527	.13	353	.17	

Note. Persisting in STEM refers to students who remained in a STEM field at the fourth year of college. Leaving STEM refers to students who left STEM fields by the fourth year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA.

Table 11

Descriptive Statistics for Predictors by Gender in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	Men (*N* = 761)		Women (*N* = 1,048)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	637.88	81.05	604.64	86.87	0.39
SAT tilt[a]	-49.29	76.04	-14.60	71.65	-0.47
High school achievement	0.42	0.72	0.46	0.62	-0.07
High school STEM coursework	0.63	1.04	0.56	0.93	0.07
High school extracurricular activities and awards in STEM	0.31	1.14	0.19	1.05	0.11
Self-rated STEM ability	3.52	0.54	3.31	0.61	0.35
High school interest in STEM	2.10	2.38	2.02	2.38	0.03
Undergraduate STEM GPA	3.09	0.63	3.02	0.64	0.12
Undergraduate GPA tilt[b]	0.36	0.42	0.51	0.43	-0.34
SES	0.32	0.76	0.16	0.81	0.20
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	594	.78	834	.80	
Bachelor's degree	167	.22	214	.20	
Race/ethnicity					
White	487	.64	683	.65	
Black	27	.04	74	.07	
Hispanic	52	.07	63	.06	
Asian	169	.22	181	.17	
Other	26	.03	47	.04	
Persistence in STEM					
Persisting	623	.82	855	.82	
Leaving	138	.18	193	.18	

Note. Persisting in STEM refers to students who remained in a STEM field at the fourth year of college. Leaving STEM refers to students who left STEM fields by the fourth year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA.

Table 12

Descriptive Statistics for Predictors by Gender in Sample of Second Year Undergraduates Majoring in Male-Dominated STEM Fields

	Men (N = 3,386)		Women (N = 996)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	656.96	75.76	639.52	80.92	0.23
SAT tilt[a]	-66.58	79.06	-46.52	79.72	-0.25
High school achievement	0.36	0.70	0.53	0.62	-0.26
High school STEM coursework	0.67	1.08	0.69	1.01	-0.02
High school STEM coursework (excluding biological sciences)	0.71	1.09	0.71	1.00	0.00
High school extracurricular activities and awards in STEM	0.48	1.27	0.39	1.20	0.07
Self-rated STEM ability	3.57	0.53	3.43	0.57	0.26
High school interest in STEM	3.47	2.25	2.68	2.41	0.35
High school interest in STEM (excluding biological sciences)	3.32	2.31	2.31	2.41	0.44
Undergraduate STEM GPA	2.95	0.65	3.03	0.65	-0.13
Undergraduate GPA tilt[b]	0.37	0.48	0.45	0.48	-0.17
SES	0.25	0.74	0.28	0.77	-0.04
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	2,129	.63	663	.67	
Bachelor's degree	1,257	.37	333	.33	
Race/ethnicity					
White	2,595	.77	692	.69	
Black	143	.04	65	.07	
Hispanic	178	.05	48	.05	
Asian	387	.11	156	.16	
Other	83	.02	35	.04	
Persistence in STEM					
Persisting	2,997	.89	836	.84	
Leaving	389	.11	160	.16	
Persistence in male-dominated STEM					
Persisting	2,963	.88	802	.81	
Leaving	423	.12	194	.19	

[a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA.

Table 13

Descriptive Statistics for Predictors by Gender in Multiple-year Longitudinal Sample

	Men (N = 3,134)		Women (N = 1,772)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	645.34	82.43	609.00	87.25	0.43
SAT tilt[a]	-57.08	80.51	-21.51	77.44	-0.45
High school achievement	0.37	0.71	0.49	0.62	-0.17
High school STEM coursework	0.68	1.08	0.62	0.98	0.05
High school extracurricular activities and awards in STEM	0.48	1.30	0.29	1.11	0.15
Self-rated STEM ability	3.56	0.53	3.33	0.60	0.40
High school interest in STEM	4.78	0.58	4.59	0.80	0.28
Freshman STEM GPA	2.99	0.73	3.00	0.75	-0.01
Undergraduate STEM GPA through year 2	2.93	0.69	2.97	0.69	-0.06
Undergraduate STEM GPA through year 3	2.93	0.67	2.99	0.67	-0.09
Freshman GPA tilt[b]	0.29	0.63	0.42	0.64	-0.20
Undergraduate GPA tilt through year 2[c]	0.35	0.53	0.46	0.53	-0.20
Undergraduate GPA tilt through year 3[d]	0.36	0.48	0.45	0.49	-0.17
SES	0.23	0.76	0.16	0.83	0.10
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	2,094	.67	1,305	.74	
Bachelor's degree	1,040	.33	467	.26	
Race/ethnicity					
White	2,266	.72	1,185	.67	
Black	161	.05	155	.09	
Hispanic	237	.08	145	.08	
Asian	387	.12	230	.13	
Other	83	.03	57	.03	
Persistence in STEM					
Persisting through year 2	2,139	.68	887	.50	
Persisting through year 3	2,044	.65	800	.45	
Persisting through year 4	1,962	.63	793	.45	

[a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA. [c]Cumulative non-STEM GPA through year 2 minus cumulative STEM GPA through year 2. [d]Cumulative non-STEM GPA through year 3 minus cumulative STEM GPA through year 3.

Table 14

Summary Table: Persistence *d*-values and Odds Ratios in All High School and Second Year Samples

	HS – STEM[a]	HS – Biological Sciences[a]	HS – Male-dominated STEM[a]	HS – Male-dominated STEM[b]	Year 2 – STEM[a]	Year 2 – Biological Sciences[a]	Year 2 – Male-dominated STEM[a]	Year 2 – Male-dominated STEM[b]
	d	*d*	*d*		*d*	*d*	*d*	*d*
SAT-Math	0.78	0.48	0.88	0.93	0.40	0.31	0.44	0.40
SAT tilt[c]	-0.46	-0.19	-0.58	-0.63	-0.21	-0.15	-0.23	-0.18
High school achievement	0.42	0.29	0.42	0.39	0.30	0.25	0.31	0.34
High school STEM coursework	0.55	0.27	0.63	0.63	0.23	0.13	0.28	0.28
High school extracurricular activities and awards in STEM	0.46	0.19	0.57	0.61	0.07	-0.04	0.09	0.10
Self-rated STEM ability	0.75	0.40	0.83	0.83	0.30	0.17	0.35	0.35
High school interest in STEM	0.08	-0.01	0.23	0.34	0.25	0.09	0.32	0.27
Undergraduate STEM GPA	0.19	0.34	0.16	0.15	0.57	0.48	0.60	0.64
Undergraduate GPA tilt[d]	-0.03	-0.12	-0.04	-0.07	-0.29	-0.26	-0.27	-0.29
SES	0.19	0.17	0.18	0.19	0.06	0.07	0.06	0.05
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
Degree goal[e]	1.30	1.51	1.12	1.00	1.20	1.30	1.18	1.30
Gender[f]	3.10	1.62	4.77	6.20	1.43	1.02	1.69	1.47
Race/ethnicity								
Black[g]	1.21	1.15	1.25	1.33	1.59	1.40	1.62	1.63
Hispanic[h]	1.28	1.40	1.25	1.32	1.12	1.06	0.98	1.07
Asian[i]	0.48	0.71	0.47	0.53	0.95	0.69	1.14	1.08
Other[j]	0.83	0.97	0.90	0.96	1.02	0.75	1.31	1.15

Note. HS = sample with high school seniors interested in STEM. Year 2 = sample with second year undergraduates choosing a STEM major. Positive *d*s indicate that those persisting had higher values than those leaving; negative *d*s indicate that those leaving had higher values than those persisting. [a]The outcome is persistence in any STEM field, and all predictors include all STEM fields. [b]The outcome is persistence in male-dominated STEM fields, and high school STEM coursework and interest exclude biological sciences. [c]SAT-Critical Reading minus SAT-Math. [d]Non-STEM GPA minus STEM GPA. [e]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [f]odds of persistence for males to odds of persistence for females. [g]odds of persistence for Whites to odds of persistence for Blacks. [h]odds of persistence for Whites to odds of persistence for Hispanics. [i]odds of persistence for Whites to odds of persistence for Asians. [j]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 15

Descriptive Statistics for Predictors by Persistence in Sample of High School Seniors Interested in STEM Fields

	Persisting in STEM (N = 11,317)		Leaving STEM (N = 22,567)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	635.40	85.87	567.23	88.21	0.78
SAT tilt[a]	-41.40	81.23	-4.84	79.07	-0.46
High school achievement	0.38	0.70	0.04	0.83	0.42
High school STEM coursework	0.51	0.94	0.06	0.75	0.55
High school extracurricular activities and awards in STEM	0.46	1.28	0.00	0.81	0.46
Self-rated STEM ability	3.47	0.57	2.99	0.67	0.75
High school interest in STEM	4.33	0.99	4.26	1.00	0.08
Freshman STEM GPA	3.01	0.73	2.85	0.84	0.19
Freshman GPA tilt[b]	0.34	0.62	0.36	0.68	-0.03
SES	0.13	0.81	-0.02	0.84	0.19
	N Persisting in STEM Major	Proportion of Group Persisting in STEM Major	*N* Leaving STEM Major	Proportion of Group Leaving STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 22,204)	7,853	.35	14,351	.65	
Bachelor's degree (N = 11,680)	3,464	.30	8,216	.70	1.30[c]
Gender					
Male (N = 15,830)	7,361	.47	8,469	.53	
Female (N = 18,054)	3,956	.22	14,098	.78	3.10[d]
Race/ethnicity					
White (N = 24,402)	7,903	.32	16,499	.68	
Black (N = 2,302)	651	.28	1,651	.72	1.21[e]
Hispanic (N = 3,041)	827	.27	2,214	.73	1.28[f]
Asian (N = 3,192)	1,589	.50	1,603	.50	0.48[g]
Other (N = 947)	347	.37	600	.63	0.83[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 16

Descriptive Statistics for Predictors by Persistence in Sample of High School Seniors Interested in Biological Science Fields

	Persisting in STEM (N = 3,723)		Leaving STEM (N = 3,684)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	619.85	86.15	577.85	87.63	0.48
SAT tilt[a]	-20.22	77.77	-5.61	76.94	-0.19
High school achievement	0.44	0.65	0.24	0.74	0.29
High school STEM coursework	0.53	0.86	0.30	0.86	0.27
High school extracurricular activities and awards in STEM	0.29	1.15	0.10	0.92	0.19
Self-rated STEM ability	3.45	0.57	3.20	0.63	0.40
High school interest in STEM	3.87	1.21	3.88	1.16	-0.01
Freshman STEM GPA	3.03	0.71	2.77	0.82	0.34
Freshman GPA tilt[b]	0.41	0.58	0.48	0.68	-0.12
SES	0.17	0.81	0.03	0.84	0.17
	N Persisting in STEM Major	Proportion of Group Persisting in STEM Major	*N* Leaving STEM Major	Proportion of Group Leaving STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 5,770)	3,030	.53	2,740	.47	
Bachelor's degree (N = 1,637)	693	.42	944	.58	1.51[c]
Gender					
Male (N = 2,714)	1,570	.58	1,144	.42	
Female (N = 4,693)	2,153	.46	2,540	.54	1.62[d]
Race/ethnicity					
White (N = 4,958)	2,474	.50	2,484	.50	
Black (N = 490)	227	.46	263	.54	1.15[e]
Hispanic (N = 606)	252	.42	354	.58	1.40[f]
Asian (N = 1,079)	631	.58	448	.42	0.71[g]
Other (N = 274)	139	.51	135	.49	0.97[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 17

Descriptive Statistics for Predictors by STEM Persistence in Sample of High School Seniors Interested in Male-dominated STEM Fields

	Persisting in STEM (N = 8,013)		Leaving STEM (N = 19,275)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	642.41	84.85	565.43	88.28	0.88
SAT tilt[a]	-50.81	80.91	-4.67	79.45	-0.58
High school achievement	0.35	0.72	0.01	0.84	0.42
High school STEM coursework	0.52	0.99	0.01	0.72	0.63
High school extracurricular activities and awards in STEM	0.53	1.33	-0.02	0.79	0.57
Self-rated STEM ability	3.49	0.56	2.96	0.67	0.83
High school interest in STEM	4.53	0.80	4.32	0.96	0.23
Freshman STEM GPA	3.00	0.73	2.87	0.84	0.16
Freshman GPA tilt[b]	0.31	0.63	0.33	0.68	-0.04
SES	0.12	0.81	-0.03	0.83	0.18

	N Persisting in STEM Major	Proportion of Group Persisting in STEM Major	N Leaving STEM Major	Proportion of Group Leaving STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 17,029)	5,149	.30	11,880	.70	
Bachelor's degree (N = 10,259)	2,864	.28	7,395	.72	1.12[c]
Gender					
Male (N = 13,503)	6,023	.45	7,480	.55	
Female (N = 13,785)	1,990	.14	11,795	.86	4.77[d]
Race/ethnicity					
White (N = 20,016)	5,720	.29	14,296	.71	
Black (N = 1,869)	454	.24	1,415	.76	1.25[e]
Hispanic (N = 2,501)	605	.24	1,896	.76	1.25[f]
Asian (N = 2,209)	1,020	.46	1,189	.54	0.47[g]
Other (N = 693)	214	.31	479	.69	0.90[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 18

Descriptive Statistics for Predictors by Male-dominated STEM Persistence in Sample of High School Seniors Interested in Male-dominated STEM Fields

	Persisting in male-dominated STEM (N = 6,850)		Leaving male-dominated STEM (N = 20,438)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	648.58	82.73	567.74	88.76	0.93
SAT tilt[a]	-55.92	80.14	-5.59	79.50	-0.63
High school achievement	0.35	0.72	0.03	0.84	0.39
High school STEM coursework (excluding biological sciences)	0.55	1.01	0.03	0.74	0.63
High school extracurricular activities and awards in STEM	0.59	1.37	-0.01	0.81	0.61
Self-rated STEM ability	3.51	0.55	2.98	0.67	0.83
High school interest in STEM (excluding biological sciences)	4.62	0.73	4.30	0.96	0.34
Freshman STEM GPA	3.00	0.73	2.88	0.84	0.15
Freshman GPA tilt[b]	0.29	0.63	0.34	0.67	-0.07
SES	0.13	0.80	-0.03	0.84	0.19
	N Persisting in Male-dominated STEM Major	Proportion of Group Persisting in Male-dominated STEM Major	*N* Leaving Male-dominated STEM Major	Proportion of Group Leaving Male-dominated STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 17,029)	4,279	.25	12,750	.75	
Bachelor's degree (N = 10,259)	2,571	.25	7,688	.75	1.00[c]
Gender					
Male (N = 13,503)	5,481	.41	8,022	.59	
Female (N = 13,785)	1,369	.10	12,416	.90	6.20[d]
Race/ethnicity					
White (N = 20,016)	4,954	.25	15,062	.75	
Black (N = 1,869)	370	.20	1,499	.80	1.33[e]
Hispanic (N = 2,501)	499	.20	2,002	.80	1.32[f]
Asian (N = 2,209)	850	.38	1,359	.62	0.53[g]
Other (N = 693)	177	.26	516	.74	0.96[h]

Note. Persisting refers to students who remained in a male-dominated STEM field at the second year of college. Leaving refers to students who left male-dominated STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 19

Descriptive Statistics for Predictors by Persistence in Sample of Second Year Undergraduates Majoring in STEM Fields

	Persisting in STEM (N = 5,311)		Leaving STEM (N = 880)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	647.55	78.74	615.23	91.51	0.40
SAT tilt[a]	-54.77	79.44	-38.25	80.92	-0.21
High school achievement	0.44	0.66	0.24	0.75	0.30
High school STEM coursework	0.68	1.05	0.44	0.97	0.23
High school extracurricular activities and awards in STEM	0.41	1.23	0.32	1.11	0.07
Self-rated STEM ability	3.52	0.55	3.35	0.62	0.30
High school interest in STEM	3.02	2.38	2.41	2.43	0.25
Undergraduate STEM GPA	3.04	0.61	2.68	0.76	0.57
Undergraduate GPA tilt[b]	0.39	0.45	0.52	0.54	-0.29
SES	0.25	0.76	0.21	0.76	0.06
	N Persisting in STEM Major	Proportion of Group Persisting in STEM Major	N Leaving STEM Major	Proportion of Group Leaving STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 4,220)	3,651	.87	569	.13	
Bachelor's degree (N = 1,971)	1,660	.84	311	.16	1.20[c]
Gender					
Male (N = 4,147)	3,620	.87	527	.13	
Female (N = 2,044)	1,691	.83	353	.17	1.43[d]
Race/ethnicity					
White (N = 4,457)	3,838	.86	619	.14	
Black (N = 309)	246	.80	63	.20	1.59[e]
Hispanic (N = 341)	289	.85	52	.15	1.12[f]
Asian (N = 893)	774	.87	119	.13	0.95[g]
Other (N = 191)	164	.86	27	.14	1.02[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the fourth year of college. Leaving STEM refers to students who left STEM fields by the fourth year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 20

Descriptive Statistics for Predictors by Persistence in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	Persisting in STEM (N = 1,478)		Leaving STEM (N = 331)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	623.46	83.28	597.01	94.51	0.31
SAT tilt[a]	-31.22	74.34	-20.12	79.86	-0.15
High school achievement	0.47	0.64	0.31	0.72	0.25
High school STEM coursework	0.61	0.98	0.49	0.99	0.13
High school extracurricular activities and awards in STEM	0.23	1.08	0.27	1.10	-0.04
Self-rated STEM ability	3.42	0.58	3.32	0.65	0.17
High school interest in STEM	2.09	2.39	1.89	2.34	0.09
Undergraduate STEM GPA	3.11	0.60	2.81	0.74	0.48
Undergraduate GPA tilt[b]	0.42	0.41	0.54	0.50	-0.26
SES	0.24	0.79	0.19	0.80	0.07

	N Persisting in STEM Major	Proportion of Group Persisting in STEM Major	*N* Leaving STEM Major	Proportion of Group Leaving STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 1,428)	1,179	.83	249	.17	
Bachelor's degree (N = 381)	299	.78	82	.22	1.30[c]
Gender					
Male (N = 761)	623	.82	138	.18	
Female (N = 1,048)	855	.82	193	.18	1.02[d]
Race/ethnicity					
White (N = 1,170)	947	.81	223	.19	
Black (N = 101)	76	.75	25	.25	1.40[e]
Hispanic (N = 115)	92	.80	23	.20	1.06[f]
Asian (N = 350)	301	.86	49	.14	0.69[g]
Other (N = 73)	62	.85	11	.15	0.75[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the fourth year of college. Leaving STEM refers to students who left STEM fields by the fourth year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 21

Descriptive Statistics for Predictors by STEM Persistence in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	Persisting in STEM (N = 3,833)		Leaving STEM (N = 549)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	656.83	74.89	626.21	87.93	0.40
SAT tilt[a]	-63.86	79.48	-49.18	79.66	-0.18
High school achievement	0.43	0.67	0.20	0.77	0.34
High school STEM coursework	0.74	1.08	0.44	0.98	0.28
High school extracurricular activities and awards in STEM	0.48	1.27	0.35	1.12	0.10
Self-rated STEM ability	3.56	0.53	3.37	0.60	0.35
High school interest in STEM	3.17	2.35	2.53	2.43	0.27
Undergraduate STEM GPA	3.02	0.62	2.61	0.76	0.64
Undergraduate GPA tilt[b]	0.37	0.47	0.51	0.56	-0.29
SES	0.26	0.75	0.22	0.73	0.05
	N Persisting in STEM Major	Proportion of Group Persisting in STEM Major	*N* Leaving STEM Major	Proportion of Group Leaving STEM Major	Odds Ratio
Degree goal					
Graduate degree (N = 2,792)	2,472	.89	320	.11	
Bachelor's degree (N = 1,590)	1,361	.86	229	.14	1.30[c]
Gender					
Male (N = 3,386)	2,997	.89	389	.11	
Female (N = 996)	836	.84	160	.16	1.47[d]
Race/ethnicity					
White (N = 3,287)	2,891	.88	396	.12	
Black (N = 208)	170	.82	38	.18	1.63[e]
Hispanic (N = 226)	197	.87	29	.13	1.07[f]
Asian (N = 543)	473	.87	70	.13	1.08[g]
Other (N = 118)	102	.86	16	.14	1.15[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the fourth year of college. Leaving STEM refers to students who left STEM fields by the fourth year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 22

Descriptive Statistics for Predictors by Male-dominated STEM Persistence in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	Persisting in Male-dominated STEM (*N* = 3,765)		Leaving Male-dominated STEM (*N* = 617)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	657.69	74.36	624.36	88.02	0.44
SAT tilt[a]	-64.58	79.24	-46.35	80.39	-0.23
High school achievement	0.43	0.67	0.22	0.76	0.31
High school STEM coursework (excluding biological sciences)	0.75	1.08	0.45	0.97	0.28
High school extracurricular activities and awards in STEM	0.48	1.27	0.36	1.13	0.09
Self-rated STEM ability	3.57	0.53	3.38	0.60	0.35
High school interest in STEM (excluding biological sciences)	3.20	2.34	2.45	2.43	0.32
Undergraduate STEM GPA	3.02	0.62	2.64	0.76	0.60
Undergraduate GPA tilt[b]	0.37	0.47	0.50	0.55	-0.27
SES	0.26	0.75	0.22	0.74	0.06

	N Persisting in Male-dominated STEM Major	Proportion of Group Persisting in Male-dominated STEM Major	*N* Leaving Male-dominated STEM Major	Proportion of Group Leaving Male-dominated STEM Major	Odds Ratio
Degree goal					
Graduate degree (*N* = 2,792)	2,420	.87	372	.13	
Bachelor's degree (*N* = 1,590)	1,345	.85	245	.15	1.18[c]
Gender					
Male (*N* = 3,386)	2,963	.88	423	.12	
Female (*N* = 996)	802	.81	194	.19	1.69[d]
Race/ethnicity					
White (*N* = 3,287)	2,844	.87	443	.13	
Black (*N* = 208)	166	.80	42	.20	1.62[e]
Hispanic (*N* = 226)	196	.87	30	.13	0.98[f]
Asian (*N* = 543)	461	.85	82	.15	1.14[g]
Other (*N* = 118)	98	.83	20	.17	1.31[h]

Note. Persisting refers to students who remained in a male-dominated STEM field at the fourth year of college. Leaving refers to students who left male-dominated STEM fields by the fourth year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table 23

Correlations among Individual-level Study Variables in Sample of High School Seniors Interested in STEM Fields

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	SAT-Math	590.00	93.15																
2	SAT tilt[a]	-17.05	81.64	-.44															
3	High school achievement	0.15	0.81	.45	-.12														
4	High school STEM coursework	0.21	0.84	.42	-.16	.33													
5	High school extracurricular activities and awards in STEM	0.15	1.01	.24	-.09	.15	.25												
6	Self-rated STEM ability	3.15	0.68	.61	-.24	.56	.41	.24											
7	High school interest in STEM	4.28	1.00	-.01	-.06	-.04	-.02	.03	-.03										
8	Degree goal_Graduate degree[b]	0.66	0.48	.09	.01	.15	.14	.08	.16	-.04									
9	Gender_Male[c]	0.47	0.50	.27	-.19	-.02	.09	.15	.25	.05	-.01								
10	Race/ethnicity_Black[d]	0.07	0.25	-.22	.05	-.12	-.06	-.03	-.11	-.01	.06	-.05							
11	Race/ethnicity_Hispanic[e]	0.09	0.29	-.14	.01	-.02	-.04	-.02	-.07	-.02	.05	-.01	-.08						
12	Race/ethnicity_Asian[f]	0.09	0.29	.19	-.17	.06	.15	.10	.08	-.03	.07	.04	-.09	-.10					
13	Race/ethnicity_Other[g]	0.03	0.16	.00	.00	.00	.02	.00	.00	-.01	.03	.00	-.04	-.05	-.05				
14	SES	0.03	0.83	.32	.01	.11	.15	.06	.21	-.01	.07	.07	-.14	-.24	-.01	-.01			
15	Freshman STEM GPA	2.90	0.81	.34	-.07	.36	.18	.06	.26	.01	.03	-.03	-.14	-.09	.04	.00	.14		
16	Freshman GPA tilt[h]	0.35	0.66	-.15	.14	-.09	-.06	-.02	-.09	-.03	.03	-.05	.04	.03	-.04	.01	-.03	-.69	
17	Persistence in STEM[i]	0.33	0.47	.35	-.21	.19	.25	.21	.33	.04	.06	.26	-.03	-.04	.11	.01	.09	.09	-.01

Note. N = 33,884. Correlations greater than .01 are significant at $p < .05$. Correlations greater than .02 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. [i]coded as 1 if the student remained in a STEM field at the second year of college and as 0 if the student left a STEM field for a non-STEM field by the second year of college.

Table 24

Correlations among Individual-level Study Variables in Sample of High School Seniors Interested in Biological Science Fields

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	SAT-Math	598.96	89.38																
2	SAT tilt[a]	-12.95	77.69	-.42															
3	High school achievement	0.34	0.70	.41	-.07														
4	High school STEM coursework	0.42	0.87	.38	-.12	.29													
5	High school extracurricular activities and awards in STEM	0.20	1.05	.19	-.04	.14	.21												
6	Self-rated STEM ability	3.33	0.62	.56	-.18	.51	.35	.21											
7	High school interest in STEM	3.87	1.18	-.02	-.01	-.04	.02	-.01	-.04										
8	Degree goal_Graduate degree[b]	0.78	0.41	.09	-.01	.13	.13	.08	.17	-.04									
9	Gender_Male[c]	0.37	0.48	.20	-.17	-.05	.04	.08	.19	.02	.01								
10	Race/ethnicity_Black[d]	0.07	0.25	-.22	.06	-.14	-.06	-.02	-.13	-.01	.07	-.04							
11	Race/ethnicity_Hispanic[e]	0.08	0.27	-.17	.03	-.05	-.07	-.03	-.11	-.01	.03	-.02	-.08						
12	Race/ethnicity_Asian[f]	0.15	0.35	.23	-.20	.07	.14	.10	.06	-.04	.07	.05	-.11	-.12					
13	Race/ethnicity_Other[g]	0.04	0.19	.00	.00	-.01	.01	-.01	.00	-.01	.03	.01	-.05	-.05	-.07				
14	SES	0.10	0.83	.33	.02	.12	.16	.06	.23	.00	.07	.08	-.12	-.21	.00	.02			
15	Freshman STEM GPA	2.90	0.78	.40	-.08	.40	.19	.08	.31	-.01	.02	.00	-.14	-.13	.08	.00	.18		
16	Freshman GPA tilt[h]	0.44	0.63	-.20	.15	-.13	-.09	-.04	-.14	.00	.02	-.07	.05	.07	-.08	.01	-.06	-.68	
17	Persistence in STEM[i]	0.50	0.50	.23	-.09	.14	.13	.09	.20	-.01	.08	.12	-.02	-.05	.07	.01	.08	.17	-.06

Note. $N = 7{,}407$. Correlations greater than .02 are significant at $p < .05$. Correlations greater than .03 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. [i]coded as 1 if the student remained in a STEM field at the second year of college and as 0 if the student left a STEM field for a non-STEM field by the second year of college.

Table 25

Correlations among Individual-level Study Variables in Sample of High School Seniors Interested in Male-dominated STEM Fields

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	SAT-Math	588.03	94.06																			
2	SAT tilt[a]	-18.22	82.59	-.45																		
3	High school achievement	0.11	0.82	.45	-.13																	
4	High school STEM coursework	0.16	0.83	.43	-.17	.32																
5	High school STEM coursework (excluding biological sciences)	0.16	0.84	.43	-.19	.32	.99															
6	High school extracurricular activities and awards in STEM	0.14	1.01	.25	-.11	.16	.27	.27														
7	Self-rated STEM ability	3.11	0.68	.62	-.26	.55	.41	.41	.25													
8	High school interest in STEM	4.40	0.90	.01	-.08	-.01	.02	.02	.05	.02												
9	High school interest in STEM (excluding biological sciences)	4.38	0.92	.01	-.08	-.01	.01	.02	.04	.01	.98											
10	Degree goal_Graduate degree[b]	0.62	0.48	.08	.01	.14	.13	.12	.07	.15	.00	.00										
11	Gender_Male[c]	0.49	0.50	.30	-.19	.00	.12	.13	.18	.29	.03	.03	.00									
12	Race/ethnicity_Black[d]	0.07	0.25	-.22	.04	-.12	-.06	-.06	-.03	-.11	-.01	-.01	.06	-.05								
13	Race/ethnicity_Hispanic[e]	0.09	0.29	-.13	.01	-.01	-.04	-.04	-.01	-.06	-.03	-.03	.06	-.01	-.09							
14	Race/ethnicity_Asian[f]	0.08	0.27	.18	-.16	.05	.13	.13	.11	.07	.00	.00	.05	.05	-.08	-.09						
15	Race/ethnicity_Other[g]	0.03	0.16	.00	.01	.00	.01	.01	.00	.00	.00	.00	.02	.00	-.04	-.05	-.04					
16	SES	0.01	0.83	.32	.01	.11	.15	.15	.06	.20	.00	.00	.07	.08	-.14	-.24	-.02	-.02				
17	Freshman STEM GPA	2.91	0.81	.33	-.06	.36	.17	.17	.06	.26	.01	.01	.03	-.03	-.14	-.08	.03	.00	.13			
18	Freshman GPA tilt[h]	0.33	0.66	-.14	.14	-.09	-.06	-.06	-.02	-.09	-.02	-.02	.02	-.04	.04	.02	-.03	.00	-.02	-.70		
19	Persistence in STEM[i]	0.29	0.46	.37	-.25	.19	.27	.27	.25	.35	.12	.11	.02	.33	-.03	-.04	.11	.01	.08	.07	-.02	
20	Persistence in male-dominated STEM[j]	0.25	0.43	.37	-.26	.17	.25	.26	.26	.34	.15	.15	.00	.35	-.03	-.04	.09	.00	.08	.07	-.03	.90

Note. $N = 27{,}288$. Correlations greater than .01 are significant at $p < .05$. Correlations greater than .02 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. [i]coded as 1 if the student remained in a STEM field at the second year of college and as 0 if the student left a STEM field for a non-STEM field by the second year of college. [j]coded as 1 if the student remained in a male-dominated STEM field at the second year of college and as 0 if the student left male-dominated STEM fields by the second year of college.

Table 26

Correlations among Individual-level Study Variables in Sample of Second Year Undergraduates Majoring in STEM Fields

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	SAT-Math	642.95	81.45																
2	SAT tilt[a]	-52.43	79.85	-.43															
3	High school achievement	0.41	0.68	.36	-.06														
4	High school STEM coursework	0.65	1.04	.35	-.11	.27													
5	High school extracurricular activities and awards in STEM	0.40	1.21	.18	-.04	.12	.24												
6	Self-rated STEM ability	3.50	0.56	.52	-.16	.49	.34	.18											
7	High school interest in STEM	2.93	2.40	.09	-.04	.05	.11	.15	.12										
8	Degree goal_Graduate degree[b]	0.68	0.47	.05	.02	.14	.15	.09	.15	.03									
9	Gender_Male[c]	0.67	0.47	.18	-.20	-.09	.02	.06	.16	.17	-.08								
10	Race/ethnicity_Black[d]	0.05	0.22	-.21	.06	-.12	-.05	-.03	-.11	.04	.08	-.06							
11	Race/ethnicity_Hispanic[e]	0.06	0.23	-.09	.01	.02	-.01	-.01	-.04	.04	.04	.00	-.06						
12	Race/ethnicity_Asian[f]	0.14	0.35	.15	-.18	.03	.13	.09	.02	-.06	.08	-.04	-.09	-.10					
13	Race/ethnicity_Other[g]	0.03	0.17	-.02	.01	-.01	.02	-.03	-.03	-.03	.04	-.03	-.04	-.04	-.07				
14	SES	0.25	0.76	.27	.03	.06	.11	.04	.17	-.02	.06	.03	-.09	-.14	-.08	.03			
15	Undergraduate STEM GPA	2.99	0.65	.38	-.06	.41	.19	.08	.30	.00	.04	-.04	-.18	-.07	.03	-.01	.12		
16	Undergraduate GPA tilt[h]	0.41	0.47	-.24	.18	-.12	-.08	-.06	-.15	-.02	.03	-.11	.11	.03	-.04	.01	-.04	-.63	
17	Persistence in STEM[i]	0.86	0.35	.14	-.07	.10	.08	.02	.11	.09	.03	.06	-.04	-.01	.01	.00	.02	.19	-.10

Note. N = 6,191. Correlations greater than .02 are significant at $p < .05$. Correlations greater than .03 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [i]coded as 1 if the student remained in a STEM major between the second and fourth years of college and as 0 if the student left a STEM major for a non-STEM major between the second and fourth years of college.

Table 27

Correlations among Individual-level Study Variables in Sample of Second Year Undergraduates Majoring in Biological Science Fields

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	SAT-Math	618.62	86.03																
2	SAT tilt[a]	-29.19	75.47	-.42															
3	High school achievement	0.44	0.66	.39	-.11														
4	High school STEM coursework	0.59	0.98	.38	-.09	.31													
5	High school extracurricular activities and awards in STEM	0.24	1.09	.18	-.04	.14	.25												
6	Self-rated STEM ability	3.40	0.59	.54	-.19	.48	.37	.20											
7	High school interest in STEM	2.05	2.38	.03	.03	.06	.12	.11	.07										
8	Degree goal_Graduate degree[b]	0.79	0.41	.05	-.05	.13	.11	.13	.15	.04									
9	Gender_Male[c]	0.42	0.49	.19	-.23	-.03	.04	.05	.17	.02	-.02								
10	Race/ethnicity_Black[d]	0.06	0.23	-.24	.05	-.16	-.09	.01	-.14	.02	.08	-.08							
11	Race/ethnicity_Hispanic[e]	0.06	0.24	-.09	.04	.01	-.04	-.01	-.04	.04	.02	.02	-.06						
12	Race/ethnicity_Asian[f]	0.19	0.40	.22	-.23	.08	.15	.11	.08	-.05	.06	.06	-.12	-.13					
13	Race/ethnicity_Other[g]	0.04	0.20	.00	.00	-.01	.01	-.05	-.04	-.02	.02	-.02	-.05	-.05	-.10				
14	SES	0.23	0.79	.33	.00	.06	.11	.05	.20	-.01	.02	.10	-.11	-.15	-.06	.03			
15	Undergraduate STEM GPA	3.05	0.64	.46	-.10	.43	.20	.05	.35	.01	.02	.06	-.19	-.12	.08	-.03	.19		
16	Undergraduate GPA tilt[h]	0.45	0.43	-.31	.18	-.18	-.10	-.03	-.21	-.03	.03	-.16	.10	.08	-.06	.00	-.10	-.68	
17	Persistence in STEM[i]	0.82	0.39	.12	-.06	.10	.05	-.02	.07	.03	.04	.00	-.04	-.01	.05	.02	.03	.18	-.10

Note. N = 1,809. Correlations greater than .04 are significant at $p < .05$. Correlations greater than .06 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [i]coded as 1 if the student remained in a STEM major between the second and fourth years of college and as 0 if the student left a STEM major for a non-STEM major between the second and fourth years of college.

Table 28

Correlations among Individual-level Study Variables in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 SAT-Math	653.00	77.30																			
2 SAT tilt[a]	-62.02	79.64	-.41																		
3 High school achievement	0.40	0.69	.36	-.05																	
4 High school STEM coursework	0.67	1.06	.33	-.10	.25																
5 High school STEM coursework (excluding biological sciences)	0.71	1.07	.34	-.11	.25	.99															
6 High school extracurricular activities and awards in STEM	0.46	1.26	.16	-.02	.12	.24	.24														
7 Self-rated STEM ability	3.54	0.54	.49	-.12	.50	.32	.32	.17													
8 High school interest in STEM	3.29	2.31	.05	.00	.05	.10	.10	.14	.11												
9 High school interest in STEM (excluding biological sciences)	3.09	2.37	.05	-.02	.05	.08	.09	.15	.11	.92											
10 Degree goal_Graduate degree[b]	0.64	0.48	.09	.01	.14	.17	.16	.10	.18	.08	.04										
11 Gender_Male[c]	0.77	0.42	.09	-.11	-.11	-.01	.00	.03	.11	.14	.18	-.03									
12 Race/ethnicity_Black[d]	0.05	0.21	-.20	.07	-.11	-.04	-.04	-.04	-.10	.05	.05	.08	-.05								
13 Race/ethnicity_Hispanic[e]	0.05	0.22	-.08	-.01	.03	.00	.00	-.01	-.04	.04	.05	.04	.01	-.05							
14 Race/ethnicity_Asian[f]	0.12	0.33	.13	-.19	.01	.13	.12	.10	.00	-.03	-.04	.08	-.05	-.08	-.09						
15 Race/ethnicity_Other[g]	0.03	0.16	-.02	.01	-.01	.03	.03	-.02	-.03	-.03	-.04	.04	-.03	-.03	-.04	-.06					
16 SES	0.25	0.75	.24	.05	.06	.11	.11	.03	.16	-.04	-.04	.08	-.02	-.09	-.13	-.09	.02				
17 Undergraduate STEM GPA	2.97	0.65	.37	-.06	.41	.18	.19	.09	.29	.01	.01	.03	-.06	-.17	-.05	.01	-.01	.09			
18 Undergraduate GPA tilt[h]	0.39	0.48	-.21	.18	-.11	-.06	-.07	-.07	-.12	.00	-.02	.02	-.07	.11	.01	-.03	.01	-.02	-.62		
19 Persistence in STEM[i]	0.87	0.33	.13	-.06	.11	.09	.09	.03	.12	.09	.09	.04	.06	-.04	.00	.00	-.01	.02	.21	-.10	
20 Persistence in male-dominated STEM[j]	0.86	0.35	.15	-.08	.11	.09	.10	.03	.12	.10	.11	.03	.08	-.04	.01	-.01	-.02	.02	.20	-.09	.93

Note. $N = 4,382$. Correlations greater than .03 are significant at $p < .05$. Correlations greater than .04 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. [i]coded as 1 if the student remained in a STEM major between the second and fourth years of college and as 0 if the student left a STEM major for a non-STEM major between the second and fourth years of college. [j]coded as 1 if the student remained in a male-dominated STEM major between the second and fourth years of college and as 0 if the student left male-dominated STEM majors between the second and fourth years of college.

Table 29

Correlations among Individual-level Study Variables in Multiple-year Longitudinal Sample

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	SAT-Math	632.21	85.99																						
2	SAT tilt[a]	-44.24	81.23	-.45																					
3	High school achievement	0.41	0.68	.35	-.08																				
4	High school STEM coursework	0.66	1.04	.38	-.13	.28																			
5	High school extracurricular activities and awards in STEM	0.41	1.24	.21	-.06	.14	.26																		
6	Self-rated STEM ability	3.48	0.57	.53	-.19	.48	.35	.20																	
7	High school interest in STEM	4.71	0.67	.09	-.03	.02	.05	.05	.14																
8	Degree goal_Graduate degree[b]	0.69	0.46	.08	.02	.15	.16	.09	.17	.01															
9	Gender_Male[c]	0.64	0.48	.20	-.21	-.08	.03	.07	.19	.13	-.07														
10	Race/ethnicity_Black[d]	0.06	0.25	-.24	.07	-.12	-.06	-.04	-.13	-.01	.06	-.07													
11	Race/ethnicity_Hispanic[e]	0.08	0.27	-.12	-.01	.04	-.02	.00	-.07	-.03	.05	-.01	-.08												
12	Race/ethnicity_Asian[f]	0.13	0.33	.19	-.19	.03	.17	.10	.03	.00	.07	-.01	-.10	-.11											
13	Race/ethnicity_Other[g]	0.03	0.17	-.01	.02	.00	.02	-.01	-.01	-.01	.04	-.01	-.04	-.05	-.06										
14	SES	0.21	0.79	.30	.03	.07	.14	.06	.20	.04	.08	.05	-.12	-.23	-.03	.02									
15	Freshman STEM GPA	2.99	0.74	.40	-.12	.37	.22	.08	.28	-.01	.07	-.01	-.14	-.08	.07	.02	.14								
16	Undergraduate STEM GPA through year 2	2.95	0.69	.39	-.10	.37	.21	.07	.28	-.01	.06	-.03	-.17	-.09	.06	.01	.15	.91							
17	Undergraduate STEM GPA through year 3	2.95	0.67	.38	-.08	.38	.20	.06	.28	-.01	.06	-.04	-.17	-.10	.06	.01	.16	.87	.97						
18	Freshman GPA tilt[h]	0.34	0.64	-.20	.20	-.10	-.10	-.05	-.12	.01	-.01	-.10	.03	.06	-.09	-.01	-.02	-.64	-.52	-.47					
19	Undergraduate GPA tilt year 2[i]	0.39	0.53	-.21	.20	-.09	-.10	-.04	-.13	.02	.01	-.10	.07	.05	-.07	.01	-.04	-.59	-.66	-.61	.78				
20	Undergraduate GPA tilt year 3[j]	0.39	0.49	-.21	.18	-.11	-.09	-.03	-.13	.02	.01	-.08	.07	.04	-.05	.00	-.04	-.57	-.65	-.67	.69	.90			
21	Persistence year 2[k]	0.62	0.49	.31	-.17	.14	.15	.13	.24	.23	.05	.18	-.04	-.06	.07	.01	.10	.17	.11	.10	-.07	.01	.04		
22	Persistence year 3[l]	0.58	0.49	.30	-.17	.14	.15	.12	.23	.21	.06	.20	-.05	-.06	.07	.01	.10	.20	.15	.13	-.09	-.02	.01	.86	
23	Persistence year 4[m]	0.56	0.50	.30	-.17	.15	.16	.11	.24	.21	.06	.17	-.04	-.05	.07	.01	.10	.21	.17	.15	-.10	-.03	.00	.82	.90

Note. N = 4,906. Correlations greater than .03 are significant at $p < .05$. Correlations greater than .04 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. [i]Cumulative non-STEM GPA through year 2 minus cumulative STEM GPA through year 2. [j]Cumulative non-STEM GPA through year 3 minus cumulative STEM GPA through year 3. [k]coded as 1 if the student remained in a STEM field at the second year of college and as 0 if the student left a STEM field for a non-STEM field by the second year of college. [l]coded as 1 if the student remained in a STEM field at the third year of college and as 0 if the student left a STEM field for a non-STEM field by the third year of college. [m]coded as 1 if the student remained in a STEM field at the fourth year of college and as 0 if the student left a STEM field for a non-STEM field by the fourth year of college.

Table 30

Correlations among School-level Study Variables in Sample of High School Seniors Interested in STEM Fields

	Variable	*Mean*	*SD*	1	2	3	4
1	Public/Private[a]	0.55	0.50				
2	Cohort SAT[b]	1031.93	129.87	.34**			
3	Admission rate[c]	0.63	0.16	-.27**	-.53**		
4	Proportion females in STEM[d]	0.48	0.14	.25*	-.28**	.00	
5	Persistence in STEM[e]	0.27	0.16	-.08	.41**	-.14	-.44**

Note. Number of schools = 98. Mean number of students per school = 346. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the second year of college. *$p < .05$. **$p < .01$.

Table 31

Correlations among School-level Study Variables in Sample of High School Seniors Interested in Biological Science Fields

	Variable	*Mean*	*SD*	1	2	3	4
1	Public/Private[a]	0.55	0.50				
2	Cohort SAT[b]	1032.26	130.50	.34**			
3	Admission rate[c]	0.63	0.16	-.27**	-.53**		
4	Proportion females in STEM[d]	0.48	0.14	.25*	-.28**	.00	
5	Persistence in STEM[e]	0.48	0.21	.01	.36**	-.14	.04

Note. Number of schools = 97. Mean number of students per school = 76. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the second year of college. *$p < .05$. **$p < .01$.

Table 32

Correlations among School-level Study Variables in Sample of High School Seniors Interested in Male-dominated STEM Fields

	Variable	*Mean*	*SD*	1	2	3	4	5
1	Public/Private[a]	0.55	0.50					
2	Cohort SAT[b]	1031.93	129.87	.34**				
3	Admission rate[c]	0.63	0.16	-.27**	-.53**			
4	Proportion females in STEM[d]	0.37	0.17	.35**	-.11	-.08		
5	Persistence in STEM[e]	0.22	0.16	-.09	.32**	-.06	-.39**	
6	Persistence in male-dominated STEM[f]	0.18	0.16	-.13	.32**	-.06	-.41**	.98**

Note. Number of schools = 98. Mean number of students per school = 278. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the second year of college. [f]proportion of students at the school persisting in male-dominated STEM fields through the end of the second year of college. $*p < .05$. $**p < .01$.

Table 33

Correlations among School-level Study Variables in Sample of Second Year Undergraduates Majoring in STEM Fields

	Variable	*Mean*	*SD*	1	2	3	4
1	Public/Private[a]	0.52	0.51				
2	Cohort SAT[b]	1052.59	115.01	.32			
3	Admission rate[c]	0.65	0.16	-.15	-.55**		
4	Proportion females in STEM[d]	0.46	0.19	.39*	-.16	-.02	
5	Persistence in STEM[e]	0.83	0.12	.13	.10	-.12	-.23

Note. Number of schools = 27. Mean number of students per school = 229. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the fourth year of college. $^*p < .05$. $^{**}p < .01$.

Table 34

Correlations among School-level Study Variables in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	Variable	*Mean*	*SD*	1	2	3	4
1	Public/Private[a]	0.52	0.51				
2	Cohort SAT[b]	1052.59	115.01	.32			
3	Admission rate[c]	0.65	0.16	-.15	-.55**		
4	Proportion females in STEM[d]	0.46	0.19	.39*	-.16	-.02	
5	Persistence in STEM[e]	0.81	0.16	.20	.32	-.35	-.19

Note. Number of schools = 27. Mean number of students per school = 67. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the fourth year of college. *$p < .05$. **$p < .01$.

Table 35

Correlations among School-level Study Variables in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	Variable	*Mean*	*SD*	1	2	3	4	5
1	Public/Private[a]	0.52	0.51					
2	Cohort SAT[b]	1052.59	115.01	.32				
3	Admission rate[c]	0.65	0.16	-.15	-.55**			
4	Proportion females in STEM[d]	0.36	0.21	.43*	-.04	-.05		
5	Persistence in STEM[e]	0.84	0.12	.15	-.17	.23	.06	
6	Persistence in male-dominated STEM[f]	0.82	0.13	.17	-.16	.15	.06	.97**

Note. Number of schools = 27. Mean number of students per school = 162. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the fourth year of college. [f]proportion of students at the school persisting in male-dominated STEM fields through the end of the fourth year of college. **p* < .05. ***p* < .01.

Table 36

Correlations among School-level Study Variables in Multiple-year Longitudinal Sample

	Variable	*Mean*	*SD*	1	2	3	4	5	6
1	Public/Private[a]	0.48	0.51						
2	Cohort SAT[b]	1042.80	111.86	.27					
3	Admission rate[c]	0.66	0.15	-.06	-.47*				
4	Proportion females in STEM[d]	0.47	0.19	.47*	-.16	-.02			
5	Persistence through year 2[e]	0.53	0.16	-.30	.34	-.08	-.12		
6	Persistence through year 3[f]	0.50	0.15	-.28	.26	-.20	-.06	.95**	
7	Persistence through year 4[g]	0.46	0.17	-.24	.41*	-.25	-.35	.82**	.82**

Note. Number of schools = 25. Mean number of students per school = 196. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the second year of college. [f]proportion of students at the school persisting in STEM through the end of the third year of college. [g]proportion of students at the school persisting in STEM through the end of the fourth year of college. *$p < .05$. **$p < .01$.

Table 37

Summary Table: Multivariate Analyses Predicting STEM Persistence using all Individual-level Predictors in All Samples

	HS – STEM[a]	HS – Biological Sciences[a]	HS – Male-dominated STEM[a]	HS – Male-dominated STEM[b]	Year 2 – STEM[a]	Year 2 – Biological Sciences[a]	Year 2 – Male-dominated STEM[a]	Year 2 – Male-dominated STEM[b]	Multiple-year Longitudinal[a]
SAT-Math	1.44**	1.37**	1.52**	1.58**	1.05M	1.08M	1.01M	1.04M	1.41**
SAT tilt[c]	0.89**	0.99	0.83**	0.81**	0.87**	0.91	0.88*	0.85**	0.88**
High school achievement	1.10**	1.07M	1.09**	1.06*	0.99M	1.04M	0.96M	0.94M	1.07*
High school STEM coursework	1.19**	1.07*	1.18**	1.15**	1.05	0.99	1.10	1.09M	1.06**
High school extracurricular activities and awards in STEM	1.16**	1.05*	1.19**	1.20**	0.94*	0.92	0.95	0.94*	1.10**
Self-rated STEM ability	1.39**	1.13**	1.37**	1.33**	1.01	0.94	1.04	1.03	1.09**
High school interest in STEM	1.00	1.00	1.20**	1.36**	1.22**	1.13	1.21**	1.25**	1.45**
Degree goal_Graduate degree[d]	1.04	1.33**	0.94**	0.88**	1.13	1.37	1.14	1.05	1.16**
Gender_Male[e]	1.96**	1.43**	2.61**	3.20**	1.39**	1.04	1.52**	1.66**	1.73**
Race/ethnicity_Black[f]	1.59**	1.45**	1.66**	1.61**	0.92	0.97	0.90	0.89	1.43**
Race/ethnicity_Hispanic[g]	1.25**	1.13	1.30**	1.18*	0.84M	0.84	0.82	0.88	1.01
Race/ethnicity_Asian[h]	1.56**	1.31**	1.45**	1.14*	0.87	1.25	0.78	0.74*	1.24*
Race/ethnicity_Other[i]	1.42**	1.18	1.37**	1.25*	1.09	1.39	0.86	0.81	1.38*
SES	1.00	1.01	0.98	0.95	0.97	1.00	0.96	0.97	1.02
Undergraduate STEM GPA	1.08	1.34**	1.03	0.98	1.90**	1.66**	2.09**	1.99**	1.43**
Undergraduate GPA tilt[j]	1.17**	1.20**	1.13**	1.04	1.19*	1.21*	1.19	1.19	1.27**

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Coefficients reflect exponentiation of unstandardized coefficient (unstandardized odds ratios) for degree goal, gender, and race/ethnicity. Coefficients reflect exponentiation of standardized coefficient (standardized odds ratios) for all other predictors. [a]Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field and 1 = the student remained in a STEM field. [b]Dependent variable is male-dominated STEM persistence, where 0 = the student left a male-dominated STEM field and 1 = the student remained in a male-dominated STEM field. [c]SAT-Critical Reading minus SAT-Math. [d]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [e]coded as 1 if student was male and 0 if student was female. [f]coded as1 if student was Black and 0 if student was any other race/ethnicity. [g]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [h]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [i]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [j]Non-STEM GPA minus STEM GPA. **p* < .05. ***p* < .01. M = predictor is mediated by STEM GPA (i.e., it is a significant predictor of STEM GPA and is a significant predictor of persistence only when undergraduate STEM GPA is excluded as a predictor).

Table 38

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.44
SAT tilt[a]	-0.00**	(0.00)	1.00	0.89
High school achievement	0.11**	(0.02)	1.12	1.10
High school STEM coursework	0.21**	(0.02)	1.23	1.19
High school extracurricular activities and awards in STEM	0.15**	(0.01)	1.16	1.16
Self-rated STEM ability	0.48**	(0.03)	1.62	1.39
High school interest in STEM	0.00	(0.04)	1.00	1.00
Degree goal_Graduate degree[b]	0.04	(0.03)	1.04	1.02
Gender_Male[c]	0.67**	(0.05)	1.96	1.40
Race/ethnicity_Black[d]	0.46**	(0.06)	1.59	1.12
Race/ethnicity_Hispanic[e]	0.22**	(0.06)	1.25	1.07
Race/ethnicity_Asian[f]	0.44**	(0.06)	1.56	1.14
Race/ethnicity_Other[g]	0.35**	(0.07)	1.42	1.05
SES	0.00	(0.02)	1.00	1.00
Freshman STEM GPA	0.09	(0.06)	1.10	1.08
Freshman GPA tilt[h]	0.23**	(0.04)	1.26	1.17

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table 39

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Biological Science Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.37
SAT tilt[a]	-0.00	(0.00)	1.00	0.99
High school achievement	0.10	(0.06)	1.10	1.07
High school STEM coursework	0.08*	(0.03)	1.08	1.07
High school extracurricular activities and awards in STEM	0.05*	(0.02)	1.05	1.05
Self-rated STEM ability	0.20**	(0.06)	1.22	1.13
High school interest in STEM	0.00	(0.02)	1.00	1.00
Degree goal_Graduate degree[b]	0.28**	(0.08)	1.33	1.12
Gender_Male[c]	0.36**	(0.05)	1.43	1.19
Race/ethnicity_Black[d]	0.37**	(0.10)	1.45	1.10
Race/ethnicity_Hispanic[e]	0.13	(0.10)	1.13	1.04
Race/ethnicity_Asian[f]	0.27**	(0.09)	1.31	1.10
Race/ethnicity_Other[g]	0.16	(0.11)	1.18	1.03
SES	0.02	(0.04)	1.02	1.01
Freshman STEM GPA	0.38**	(0.11)	1.46	1.34
Freshman GPA tilt[h]	0.28**	(0.08)	1.33	1.20

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table 40

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.52
SAT tilt[a]	-0.00**	(0.00)	1.00	0.83
High school achievement	0.11**	(0.03)	1.12	1.09
High school STEM coursework	0.20**	(0.03)	1.22	1.18
High school extracurricular activities and awards in STEM	0.18**	(0.02)	1.19	1.19
Self-rated STEM ability	0.46**	(0.03)	1.59	1.37
High school interest in STEM	0.20**	(0.05)	1.22	1.20
Degree goal_Graduate degree[b]	-0.13**	(0.03)	0.88	0.94
Gender_Male[c]	0.96**	(0.05)	2.61	1.62
Race/ethnicity_Black[d]	0.51**	(0.08)	1.66	1.14
Race/ethnicity_Hispanic[e]	0.26**	(0.07)	1.30	1.08
Race/ethnicity_Asian[f]	0.37**	(0.07)	1.45	1.11
Race/ethnicity_Other[g]	0.32**	(0.08)	1.37	1.05
SES	-0.02	(0.02)	0.98	0.98
Freshman STEM GPA	0.04	(0.05)	1.04	1.03
Freshman GPA tilt[h]	0.19**	(0.05)	1.21	1.13

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table 41

Logistic Regression Analysis using all Individual-level Predictors: Predicting Male-dominated STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.58
SAT tilt[a]	-0.00**	(0.00)	1.00	0.81
High school achievement	0.07*	(0.03)	1.08	1.06
High school STEM coursework (excluding biological sciences)	0.16**	(0.03)	1.18	1.15
High school extracurricular activities and awards in STEM	0.18**	(0.02)	1.20	1.20
Self-rated STEM ability	0.42**	(0.04)	1.52	1.33
High school interest in STEM (excluding biological sciences)	0.34**	(0.05)	1.40	1.36
Degree goal_Graduate degree[b]	-0.25**	(0.04)	0.78	0.88
Gender_Male[c]	1.16**	(0.07)	3.20	1.79
Race/ethnicity_Black[d]	0.48**	(0.09)	1.61	1.13
Race/ethnicity_Hispanic[e]	0.17*	(0.07)	1.18	1.05
Race/ethnicity_Asian[f]	0.13*	(0.06)	1.14	1.04
Race/ethnicity_Other[g]	0.22*	(0.10)	1.25	1.03
SES	-0.05	(0.02)	0.95	0.96
Freshman STEM GPA	-0.02	(0.05)	0.98	0.98
Freshman GPA tilt[h]	0.06	(0.06)	1.07	1.04

Note. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM fields by the second year of college and 1 = the student remained in a male-dominated STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. *$p < .05$. **$p < .01$.

Table 42

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00	(0.00)	1.00	1.05
SAT tilt[a]	-0.00**	(0.00)	1.00	0.87
High school achievement	-0.02	(0.05)	0.98	0.99
High school STEM coursework	0.04	(0.05)	1.04	1.05
High school extracurricular activities and awards in STEM	-0.05*	(0.03)	0.95	0.94
Self-rated STEM ability	0.01	(0.07)	1.01	1.01
High school interest in STEM	0.08**	(0.02)	1.08	1.22
Degree goal_Graduate degree[b]	0.12	(0.09)	1.13	1.06
Gender_Male[c]	0.33**	(0.09)	1.39	1.17
Race/ethnicity_Black[d]	-0.09	(0.19)	0.92	0.98
Race/ethnicity_Hispanic[e]	-0.17	(0.11)	0.84	0.96
Race/ethnicity_Asian[f]	-0.14	(0.10)	0.87	0.95
Race/ethnicity_Other[g]	0.09	(0.21)	1.09	1.01
SES	-0.04	(0.04)	0.96	0.97
Undergraduate STEM GPA	0.99**	(0.13)	2.68	1.90
Undergraduate GPA tilt[h]	0.37*	(0.18)	1.45	1.19

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. *$p < .05$. **$p < .01$.

Table 43

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00	(0.00)	1.00	1.08
SAT tilt[a]	-0.00	(0.00)	1.00	0.91
High school achievement	0.06	(0.12)	1.06	1.04
High school STEM coursework	-0.01	(0.09)	0.99	0.99
High school extracurricular activities and awards in STEM	-0.07	(0.05)	0.93	0.92
Self-rated STEM ability	-0.10	(0.12)	0.91	0.94
High school interest in STEM	0.05	(0.04)	1.05	1.13
Degree goal_Graduate degree[b]	0.32	(0.18)	1.37	1.14
Gender_Male[c]	0.04	(0.11)	1.04	1.02
Race/ethnicity_Black[d]	-0.03	(0.27)	0.97	0.99
Race/ethnicity_Hispanic[e]	-0.18	(0.26)	0.84	0.96
Race/ethnicity_Asian[f]	0.22	(0.17)	1.25	1.09
Race/ethnicity_Other[g]	0.33	(0.51)	1.39	1.06
SES	0.00	(0.08)	1.00	1.00
Undergraduate STEM GPA	0.80**	(0.18)	2.22	1.66
Undergraduate GPA tilt[h]	0.44*	(0.22)	1.55	1.21

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. **p* < .05. ***p* < .01.

Table 44

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00	(0.00)	1.00	1.01
SAT tilt[a]	-0.00*	(0.00)	1.00	0.88
High school achievement	-0.06	(0.06)	0.94	0.96
High school STEM coursework	0.09	(0.05)	1.09	1.10
High school extracurricular activities and awards in STEM	-0.04	(0.03)	0.96	0.95
Self-rated STEM ability	0.08	(0.10)	1.08	1.04
High school interest in STEM	0.08**	(0.02)	1.08	1.21
Degree goal_Graduate degree[b]	0.13	(0.09)	1.14	1.07
Gender_Male[c]	0.42**	(0.10)	1.52	1.19
Race/ethnicity_Black[d]	-0.11	(0.24)	0.90	0.98
Race/ethnicity_Hispanic[e]	-0.19	(0.17)	0.82	0.96
Race/ethnicity_Asian[f]	-0.24	(0.13)	0.78	0.92
Race/ethnicity_Other[g]	-0.15	(0.28)	0.86	0.98
SES	-0.06	(0.04)	0.94	0.96
Undergraduate STEM GPA	1.13**	(0.18)	3.09	2.09
Undergraduate GPA tilt[h]	0.36	(0.21)	1.44	1.19

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. **p* < .05. ***p* < .01.

Table 45

Logistic Regression Analysis using all Individual-level Predictors: Predicting Male-dominated STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00	(0.00)	1.00	1.04
SAT tilt[a]	-0.00**	(0.00)	1.00	0.85
High school achievement	-0.09	(0.05)	0.91	0.94
High school STEM coursework (excluding biological sciences)	0.08	(0.05)	1.09	1.09
High school extracurricular activities and awards in STEM	-0.05*	(0.02)	0.95	0.94
Self-rated STEM ability	0.05	(0.08)	1.05	1.03
High school interest in STEM (excluding biological sciences)	0.09**	(0.02)	1.10	1.25
Degree goal_Graduate degree[b]	0.05	(0.08)	1.05	1.02
Gender_Male[c]	0.51**	(0.09)	1.66	1.24
Race/ethnicity_Black[d]	-0.11	(0.22)	0.89	0.98
Race/ethnicity_Hispanic[e]	-0.13	(0.16)	0.88	0.97
Race/ethnicity_Asian[f]	-0.30*	(0.13)	0.74	0.91
Race/ethnicity_Other[g]	-0.21	(0.26)	0.81	0.97
SES	-0.05	(0.04)	0.96	0.97
Undergraduate STEM GPA	1.06**	(0.17)	2.87	1.99
Undergraduate GPA tilt[h]	0.36	(0.21)	1.44	1.19

Note. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM majors between the second and fourth years of college and 1 = the student remained in a male-dominated STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Undergraduate non-STEM GPA minus undergraduate STEM GPA. *$p < .05$. **$p < .01$.

Table 46

Survival Analysis using all Individual-level Predictors: Predicting STEM Persistence in Multiple-year Longitudinal Sample

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.41
SAT tilt[a]	-0.00**	(0.00)	1.00	0.88
High school achievement	0.11*	(0.05)	1.11	1.07
High school STEM coursework	0.05**	(0.02)	1.05	1.06
High school extracurricular activities and awards in STEM	0.08**	(0.02)	1.08	1.10
Self-rated STEM ability	0.16**	(0.05)	1.17	1.09
High school interest in STEM	0.55**	(0.07)	1.73	1.45
Degree goal_Graduate degree[b]	0.15**	(0.05)	1.16	1.07
Gender_Male[c]	0.55**	(0.07)	1.73	1.30
Race/ethnicity_Black[d]	0.36**	(0.08)	1.43	1.09
Race/ethnicity_Hispanic[e]	0.01	(0.10)	1.01	1.00
Race/ethnicity_Asian[f]	0.22*	(0.09)	1.24	1.07
Race/ethnicity_Other[g]	0.32*	(0.15)	1.38	1.05
SES	0.02	(0.04)	1.02	1.02
Cumulative STEM GPA	0.49**	(0.06)	1.63	1.43
Cumulative GPA tilt[h]	0.38**	(0.04)	1.46	1.27
Time	-0.14**	(0.04)	0.87	0.89

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field and 1 = the student remained in a STEM field. *b* = unstandardized coefficient. Exp(*b*) = exponentiation of unstandardized coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Cumulative non-STEM GPA minus cumulative STEM GPA. *p < .05. **p < .01.

Table 47

Survival Analysis using all Individual-level Predictors and Time Interactions: Predicting STEM Persistence in Multiple-year Longitudinal Sample

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.41
SAT tilt[a]	-0.00**	(0.00)	1.00	0.88
High school achievement	0.10	(0.07)	1.10	1.07
High school STEM coursework	0.05	(0.04)	1.06	1.06
High school extracurricular activities and awards in STEM	0.08**	(0.03)	1.09	1.11
Self-rated STEM ability	0.16	(0.08)	1.17	1.09
High school interest in STEM	0.55**	(0.06)	1.73	1.45
Degree goal_Graduate degree[b]	0.15	(0.08)	1.16	1.07
Gender_Male[c]	0.56**	(0.08)	1.75	1.31
Race/ethnicity_Black[d]	0.36*	(0.16)	1.44	1.09
Race/ethnicity_Hispanic[e]	0.01	(0.15)	1.01	1.00
Race/ethnicity_Asian[f]	0.21	(0.12)	1.24	1.07
Race/ethnicity_Other[g]	0.32	(0.24)	1.38	1.05
SES	0.02	(0.05)	1.02	1.02
Cumulative STEM GPA	0.26**	(0.06)	1.29	1.29
Cumulative GPA tilt[h]	0.16**	(0.05)	1.17	1.17
Time	-0.14**	(0.02)	0.87	0.89
SAT-Math*Time	0.00	(0.00)	1.00	
SAT tilt*Time	0.00	(0.00)	1.00	
High school achievement*Time	-0.02	(0.04)	0.98	
High school STEM coursework*Time	0.01	(0.02)	1.01	
High school extracurricular activities and awards in STEM*Time	-0.03	(0.02)	0.97	
Self-rated STEM ability*Time	0.02	(0.05)	1.02	
High school interest in STEM*Time	-0.04	(0.04)	0.97	
Degree goal_Graduate degree*Time	0.02	(0.05)	1.02	
Gender_Male*Time	0.02	(0.05)	1.02	
Race/ethnicity_Black*Time	0.03	(0.09)	1.03	
Race/ethnicity_Hispanic*Time	0.05	(0.09)	1.05	
Race/ethnicity_Asian*Time	0.01	(0.07)	1.01	
Race/ethnicity_Other*Time	0.08	(0.14)	1.08	
SES*Time	0.00	(0.03)	1.00	
Cumulative STEM GPA*Time	0.11**	(0.03)	1.12	
Cumulative GPA tilt*Time	0.08*	(0.03)	1.08	

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field and 1 = the student remained in a STEM field. *b* = unstandardized coefficient. Exp(*b*) = exponentiation of unstandardized coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized coefficient (standardized odds ratio). Values in parentheses are standard errors. All predictors were standardized because of their inclusion in interaction terms. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Cumulative non-STEM GPA minus cumulative STEM GPA. *$p < .05$. **$p < .01$.

Table 48

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.45
SAT tilt[a]	-0.00**	(0.00)	1.00	0.91
High school achievement	0.13**	(0.02)	1.13	1.11
High school STEM coursework	0.21**	(0.02)	1.23	1.19
High school extracurricular activities and awards in STEM	0.15**	(0.01)	1.16	1.16
Self-rated STEM ability	0.48**	(0.03)	1.62	1.38
High school interest in STEM	0.00	(0.04)	1.00	1.00
Degree goal_Graduate degree[b]	0.05	(0.03)	1.05	1.02
Gender_Male[c]	0.65**	(0.05)	1.91	1.38
Race/ethnicity_Black[d]	0.46**	(0.06)	1.58	1.12
Race/ethnicity_Hispanic[e]	0.23**	(0.06)	1.25	1.07
Race/ethnicity_Asian[f]	0.44**	(0.06)	1.55	1.14
Race/ethnicity_Other[g]	0.35**	(0.07)	1.43	1.05
SES	0.00	(0.02)	1.00	1.00

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 49

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Biological Science Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.47
SAT tilt[a]	0.00	(0.00)	1.00	1.03
High school achievement	0.20**	(0.05)	1.22	1.15
High school STEM coursework	0.08*	(0.03)	1.08	1.07
High school extracurricular activities and awards in STEM	0.05	(0.02)	1.05	1.05
Self-rated STEM ability	0.20**	(0.06)	1.22	1.13
High school interest in STEM	-0.00	(0.02)	1.00	0.99
Degree goal_Graduate degree[b]	0.28**	(0.08)	1.32	1.12
Gender_Male[c]	0.31**	(0.06)	1.37	1.16
Race/ethnicity_Black[d]	0.34**	(0.10)	1.40	1.09
Race/ethnicity_Hispanic[e]	0.11	(0.10)	1.12	1.03
Race/ethnicity_Asian[f]	0.27**	(0.09)	1.31	1.10
Race/ethnicity_Other[g]	0.17	(0.11)	1.18	1.03
SES	0.03	(0.04)	1.03	1.03

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 50

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.51
SAT tilt[a]	-0.00**	(0.00)	1.00	0.85
High school achievement	0.11**	(0.03)	1.11	1.09
High school STEM coursework	0.20**	(0.03)	1.22	1.18
High school extracurricular activities and awards in STEM	0.18**	(0.02)	1.19	1.20
Self-rated STEM ability	0.46**	(0.03)	1.58	1.37
High school interest in STEM	0.20**	(0.05)	1.22	1.20
Degree goal_Graduate degree[b]	-0.13**	(0.03)	0.88	0.94
Gender_Male[c]	0.95**	(0.06)	2.58	1.61
Race/ethnicity_Black[d]	0.51**	(0.08)	1.66	1.14
Race/ethnicity_Hispanic[e]	0.27**	(0.07)	1.31	1.08
Race/ethnicity_Asian[f]	0.36**	(0.07)	1.44	1.10
Race/ethnicity_Other[g]	0.32**	(0.08)	1.37	1.05
SES	-0.02	(0.02)	0.98	0.98

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. $^*p < .05$. $^{**}p < .01$.

Table 51

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Male-dominated STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.57
SAT tilt[a]	-0.00**	(0.00)	1.00	0.81
High school achievement	0.06*	(0.03)	1.06	1.05
High school STEM coursework (excluding biological sciences)	0.16**	(0.03)	1.18	1.15
High school extracurricular activities and awards in STEM	0.18**	(0.02)	1.20	1.21
Self-rated STEM ability	0.41**	(0.04)	1.51	1.33
High school interest in STEM (excluding biological sciences)	0.33**	(0.05)	1.40	1.36
Degree goal_Graduate degree[b]	-0.25**	(0.04)	0.78	0.88
Gender_Male[c]	1.17**	(0.07)	3.21	1.79
Race/ethnicity_Black[d]	0.48**	(0.09)	1.62	1.13
Race/ethnicity_Hispanic[e]	0.17*	(0.07)	1.19	1.05
Race/ethnicity_Asian[f]	0.13*	(0.06)	1.14	1.04
Race/ethnicity_Other[g]	0.22*	(0.10)	1.25	1.03
SES	-0.05*	(0.02)	0.95	0.96

Note. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM fields by the second year of college and 1 = the student remained in a male-dominated STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 52

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.24
SAT tilt[a]	-0.00	(0.00)	1.00	0.93
High school achievement	0.23**	(0.06)	1.25	1.17
High school STEM coursework	0.05	(0.06)	1.06	1.06
High school extracurricular activities and awards in STEM	-0.05	(0.03)	0.95	0.94
Self-rated STEM ability	0.02	(0.07)	1.02	1.01
High school interest in STEM	0.07**	(0.02)	1.07	1.19
Degree goal_Graduate degree[b]	0.09	(0.08)	1.10	1.04
Gender_Male[c]	0.24*	(0.10)	1.27	1.12
Race/ethnicity_Black[d]	-0.23	(0.18)	0.80	0.95
Race/ethnicity_Hispanic[e]	-0.25*	(0.11)	0.78	0.95
Race/ethnicity_Asian[f]	-0.13	(0.10)	0.88	0.96
Race/ethnicity_Other[g]	0.00	(0.21)	1.00	1.00
SES	-0.01	(0.04)	0.99	0.99

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 53

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00*	(0.00)	1.00	1.25
SAT tilt[a]	-0.00	(0.00)	1.00	0.97
High school achievement	0.25*	(0.11)	1.28	1.18
High school STEM coursework	-0.01	(0.09)	0.99	0.99
High school extracurricular activities and awards in STEM	-0.09	(0.05)	0.92	0.91
Self-rated STEM ability	-0.08	(0.13)	0.92	0.95
High school interest in STEM	0.04	(0.04)	1.04	1.11
Degree goal_Graduate degree[b]	0.30	(0.17)	1.35	1.13
Gender_Male[c]	0.01	(0.12)	1.01	1.00
Race/ethnicity_Black[d]	-0.12	(0.27)	0.88	0.97
Race/ethnicity_Hispanic[e]	-0.28	(0.22)	0.76	0.93
Race/ethnicity_Asian[f]	0.22	(0.18)	1.24	1.09
Race/ethnicity_Other[g]	0.26	(0.57)	1.30	1.05
SES	0.03	(0.08)	1.04	1.03

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 54

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00*	(0.00)	1.00	1.20
SAT tilt[a]	-0.00	(0.00)	1.00	0.94
High school achievement	0.22**	(0.07)	1.25	1.17
High school STEM coursework	0.10*	(0.05)	1.11	1.12
High school extracurricular activities and awards in STEM	-0.03	(0.04)	0.97	0.96
Self-rated STEM ability	0.07	(0.10)	1.07	1.04
High school interest in STEM	0.07**	(0.02)	1.08	1.19
Degree goal_Graduate degree[b]	0.09	(0.09)	1.09	1.04
Gender_Male[c]	0.30**	(0.11)	1.35	1.13
Race/ethnicity_Black[d]	-0.30	(0.24)	0.74	0.94
Race/ethnicity_Hispanic[e]	-0.24	(0.21)	0.78	0.95
Race/ethnicity_Asian[f]	-0.25**	(0.10)	0.78	0.92
Race/ethnicity_Other[g]	-0.21	(0.29)	0.81	0.97
SES	-0.04	(0.04)	0.96	0.97

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 55

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Male-dominated STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.23
SAT tilt[a]	-0.00	(0.00)	1.00	0.91
High school achievement	0.17**	(0.06)	1.19	1.13
High school STEM coursework (excluding biological sciences)	0.10*	(0.05)	1.11	1.11
High school extracurricular activities and awards in STEM	-0.04	(0.03)	0.96	0.95
Self-rated STEM ability	0.05	(0.08)	1.05	1.03
High school interest in STEM (excluding biological sciences)	0.09**	(0.02)	1.09	1.23
Degree goal_Graduate degree[b]	0.01	(0.08)	1.01	1.00
Gender_Male[c]	0.39**	(0.11)	1.47	1.18
Race/ethnicity_Black[d]	-0.29	(0.21)	0.75	0.94
Race/ethnicity_Hispanic[e]	-0.18	(0.20)	0.84	0.96
Race/ethnicity_Asian[f]	-0.31**	(0.10)	0.73	0.90
Race/ethnicity_Other[g]	-0.27	(0.26)	0.76	0.96
SES	-0.03	(0.04)	0.97	0.98

Note. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM majors between the second and fourth years of college and 1 = the student remained in a male-dominated STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 56

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		β
SAT-Math	0.00**	(0.00)	0.34
SAT tilt[a]	0.00**	(0.00)	0.08
High school achievement	0.30**	(0.01)	0.30
High school STEM coursework	0.01*	(0.01)	0.01
High school extracurricular activities and awards in STEM	-0.02**	(0.00)	-0.02
Self-rated STEM ability	-0.01	(0.01)	-0.01
High school interest in STEM	0.02**	(0.00)	0.02
Degree goal_Graduate degree[b]	-0.04**	(0.01)	-0.02
Gender_Male[c]	-0.13**	(0.01)	-0.08
Race/ethnicity_Black[d]	-0.15**	(0.03)	-0.05
Race/ethnicity_Hispanic[e]	-0.08**	(0.02)	-0.03
Race/ethnicity_Asian[f]	-0.01	(0.02)	-0.00
Race/ethnicity_Other[g]	-0.03	(0.03)	-0.01
SES	0.04**	(0.01)	0.04

Note. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. β = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *p < .05. **p < .01.

Table 57

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in Biological Science Fields

	b (*SE*)		*β*
SAT-Math	0.00**	(0.00)	0.35
SAT tilt[a]	0.00**	(0.00)	0.08
High school achievement	0.33**	(0.01)	0.30
High school STEM coursework	0.01	(0.01)	0.01
High school extracurricular activities and awards in STEM	-0.01	(0.01)	-0.01
Self-rated STEM ability	0.03	(0.02)	0.02
High school interest in STEM	0.00	(0.01)	0.00
Degree goal_Graduate degree[b]	-0.06**	(0.02)	-0.03
Gender_Male[c]	-0.07**	(0.02)	-0.04
Race/ethnicity_Black[d]	-0.08	(0.05)	-0.02
Race/ethnicity_Hispanic[e]	-0.11**	(0.02)	-0.04
Race/ethnicity_Asian[f]	0.04*	(0.02)	0.02
Race/ethnicity_Other[g]	-0.01	(0.04)	-0.00
SES	0.05**	(0.01)	0.06

Note. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 58

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in Male-dominated STEM Fields (with Predictors Reflecting all STEM Fields)

	b (*SE*)		*β*
SAT-Math	0.00**	(0.00)	0.34
SAT tilt[a]	0.00**	(0.00)	0.09
High school achievement	0.29**	(0.01)	0.30
High school STEM coursework	0.02**	(0.01)	0.02
High school extracurricular activities and awards in STEM	-0.02**	(0.00)	-0.02
Self-rated STEM ability	-0.01	(0.01)	-0.01
High school interest in STEM	0.02**	(0.00)	0.02
Degree goal_Graduate degree[b]	-0.03**	(0.01)	-0.02
Gender_Male[c]	-0.15**	(0.01)	-0.09
Race/ethnicity_Black[d]	-0.17**	(0.03)	-0.05
Race/ethnicity_Hispanic[e]	-0.07**	(0.02)	-0.03
Race/ethnicity_Asian[f]	-0.02	(0.02)	-0.01
Race/ethnicity_Other[g]	-0.03	(0.03)	-0.00
SES	0.03**	(0.01)	0.03

Note. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *p < .05. **p < .01.

Table 59

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in Male-dominated STEM Fields (with Predictors Reflecting Male-dominated STEM Fields)

	b (*SE*)		*β*
SAT-Math	0.00**	(0.00)	0.34
SAT tilt[a]	0.00**	(0.00)	0.09
High school achievement	0.29**	(0.01)	0.30
High school STEM coursework (excluding biological sciences)	0.02**	(0.01)	0.02
High school extracurricular activities and awards in STEM	-0.02**	(0.00)	-0.02
Self-rated STEM ability	-0.01	(0.01)	-0.01
High school interest in STEM (excluding biological sciences)	0.02**	(0.00)	0.02
Degree goal_Graduate degree[b]	-0.03**	(0.01)	-0.02
Gender_Male[c]	-0.15**	(0.01)	-0.09
Race/ethnicity_Black[d]	-0.17**	(0.03)	-0.05
Race/ethnicity_Hispanic[e]	-0.07**	(0.02)	-0.03
Race/ethnicity_Asian[f]	-0.02	(0.02)	-0.01
Race/ethnicity_Other[g]	-0.03	(0.03)	-0.00
SES	0.03**	(0.01)	0.03

Note. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 60

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in STEM Fields

	b (*SE*)		β
SAT-Math	0.00**	(0.00)	0.32
SAT tilt[a]	0.00**	(0.00)	0.08
High school achievement	0.29**	(0.02)	0.30
High school STEM coursework	0.01	(0.01)	0.02
High school extracurricular activities and awards in STEM	0.00	(0.01)	0.00
Self-rated STEM ability	0.03	(0.02)	0.02
High school interest in STEM	-0.01*	(0.00)	-0.02
Degree goal_Graduate degree[b]	-0.03	(0.02)	-0.02
Gender_Male[c]	-0.06*	(0.02)	-0.04
Race/ethnicity_Black[d]	-0.20**	(0.04)	-0.07
Race/ethnicity_Hispanic[e]	-0.12**	(0.03)	-0.04
Race/ethnicity_Asian[f]	-0.01	(0.04)	-0.00
Race/ethnicity_Other[g]	-0.06	(0.04)	-0.02
SES	0.03*	(0.01)	0.03

Note. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. β = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *p < .05. **p < .01.

Table 61

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	b (*SE*)		β
SAT-Math	0.00**	(0.00)	0.37
SAT tilt[a]	0.00**	(0.00)	0.08
High school achievement	0.28**	(0.03)	0.30
High school STEM coursework	-0.01	(0.01)	-0.02
High school extracurricular activities and awards in STEM	-0.02**	(0.01)	-0.04
Self-rated STEM ability	0.04	(0.04)	0.04
High school interest in STEM	-0.01	(0.00)	-0.02
Degree goal_Graduate degree[b]	-0.02	(0.02)	-0.01
Gender_Male[c]	0.02	(0.03)	0.02
Race/ethnicity_Black[d]	-0.17**	(0.05)	-0.06
Race/ethnicity_Hispanic[e]	-0.22**	(0.04)	-0.08
Race/ethnicity_Asian[f]	-0.02	(0.03)	-0.01
Race/ethnicity_Other[g]	-0.12*	(0.06)	-0.04
SES	0.04**	(0.01)	0.05

Note. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. β = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 62

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields (with Predictors Reflecting all STEM Fields)

	b (*SE*)		β
SAT-Math	0.00**	(0.00)	0.30
SAT tilt[a]	0.00**	(0.00)	0.07
High school achievement	0.28**	(0.02)	0.30
High school STEM coursework	0.02	(0.01)	0.03
High school extracurricular activities and awards in STEM	0.01	(0.01)	0.02
Self-rated STEM ability	0.02	(0.02)	0.02
High school interest in STEM	0.00	(0.00)	0.00
Degree goal_Graduate degree[b]	-0.04*	(0.02)	-0.03
Gender_Male[c]	-0.08**	(0.03)	-0.05
Race/ethnicity_Black[d]	-0.22**	(0.06)	-0.07
Race/ethnicity_Hispanic[e]	-0.09*	(0.04)	-0.03
Race/ethnicity_Asian[f]	-0.03	(0.06)	-0.02
Race/ethnicity_Other[g]	-0.03	(0.05)	-0.01
SES	0.01	(0.01)	0.02

Note. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. β = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *p < .05. **p < .01.

Table 63

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields (with Predictors Reflecting Male-dominated STEM Fields)

	b (*SE*)		*β*
SAT-Math	0.00**	(0.00)	0.29
SAT tilt[a]	0.00**	(0.00)	0.07
High school achievement	0.28**	(0.02)	0.30
High school STEM coursework (excluding biological sciences)	0.02*	(0.01)	0.03
High school extracurricular activities and awards in STEM	0.01	(0.01)	0.02
Self-rated STEM ability	0.02	(0.02)	0.02
High school interest in STEM (excluding biological sciences)	0.00	(0.00)	0.00
Degree goal_Graduate degree[b]	-0.04*	(0.02)	-0.03
Gender_Male[c]	-0.08**	(0.03)	-0.05
Race/ethnicity_Black[d]	-0.22**	(0.06)	-0.07
Race/ethnicity_Hispanic[e]	-0.09*	(0.04)	-0.03
Race/ethnicity_Asian[f]	-0.03	(0.06)	-0.02
Race/ethnicity_Other[g]	-0.03	(0.05)	-0.01
SES	0.01	(0.01)	0.02

Note. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master’s or doctoral degree and 0 if student aspired to bachelor’s degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed “other” as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 64

Summary Table: Multilevel Analyses Predicting Persistence using all School- and Individual-level Predictors in All Samples

	HS – STEM[a]	HS – Biological Sciences[a]	HS – Male-dominated STEM[a]	HS – Male-dominated STEM[b]	Year 2 – STEM[a]	Year 2 – Biological Sciences[a]	Year 2 – Male-dominated STEM[a]	Year 2 – Male-dominated STEM[b]	Multiple-year Longitudinal[a]
School-level Predictors									
Public/Private[c]	0.89	0.72	1.00	0.86	1.50	1.45	1.66	1.73	0.65
Cohort SAT[d]	0.89	1.07	0.82	0.95	0.75	0.93	0.70	0.71	0.93
Admission rate[e]	1.07	1.11	1.09	1.10	0.83	0.68*	1.07	0.98	0.98
Proportion females in STEM[f]	0.98	1.35**	0.90	0.92	0.82	0.82	0.98	1.06	1.29
Individual-level Predictors									
SAT-Math	1.45**	1.38**	1.55**	1.61**	1.05M	1.06M	1.02M	1.06M	1.42**
SAT tilt[g]	0.89**	1.00	0.83**	0.81**	0.88**	0.90	0.89*	0.86**	0.88**
High school achievement	1.10**	1.08M	1.10**	1.07**	0.99M	1.04M	0.97M	0.94M	1.07*
High school STEM coursework	1.20**	1.07*	1.19**	1.15**	1.05	0.99	1.09	1.09M	1.06**
High school extracurricular activities and awards in STEM	1.16**	1.05*	1.20**	1.21**	0.94*	0.92	0.95	0.94*	1.10**
Self-rated STEM ability	1.39**	1.13**	1.38**	1.33**	1.01	0.94	1.04	1.03	1.10**
High school interest in STEM	1.00	1.00	1.20**	1.37**	1.21**	1.14	1.20**	1.24**	1.45**
Degree goal_Graduate degree[h]	1.04	1.33**	0.87**	0.77**	1.12	1.38	1.13	1.04	1.16**
Gender_Male[i]	1.70**	1.29**	2.35**	2.90**	1.09	1.05	1.17	1.04	1.22*
Race/ethnicity_Black[j]	1.61**	1.46**	1.69**	1.64**	0.93	0.96	0.93	0.92	1.46**
Race/ethnicity_Hispanic[k]	1.25**	1.14	1.31**	1.19*	0.85M	0.81	0.85	0.90	0.99
Race/ethnicity_Asian[l]	1.57**	1.33**	1.46**	1.14*	0.88	1.25	0.80	0.76*	1.25**
Race/ethnicity_Other[m]	1.43**	1.18	1.39**	1.26*	1.08	1.37	0.87	0.82	1.38*
SES	1.00	1.02	0.98	0.96*	0.97	1.00	0.96	0.97	1.02
Undergraduate STEM GPA	1.05	1.39**	0.99	0.96	2.08**	1.96**	2.25**	2.20**	1.35**
Undergraduate GPA tilt[n]	1.17**	1.20**	1.13**	1.04	1.18	1.21	1.18	1.18	1.27**
Undergraduate STEM GPA*Gender	0.06	0.00	0.07*	0.03	0.06	-0.08	0.07	0.02	0.07
Cross-level interaction									
Proportion females in STEM*Gender	-0.22**	-0.17*	-0.16	-0.18	-0.38**	0.01	-0.37	-0.78**	-0.58**

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link. Values reflect unstandardized odds ratios for degree goal, gender, and race/ethnicity. Values reflect standardized odds ratios for all other main effects. Values reflect unstandardized coefficients for interactions. [a]Dependent variable is STEM persistence, where 0 = leaving STEM and 1 = remaining in STEM. [b]Dependent variable is male-dominated STEM persistence, where 0 = leaving male-dominated STEM and 1 = remaining in male-dominated STEM. [c]0 = public and 1 = private. [d]25th percentile SAT score of entering undergraduates. [e]proportion of undergraduate applicants admitted. [f]proportion of undergraduate STEM students who are female. [g]SAT-Critical Reading minus SAT-Math. [h]1 = master's or doctoral degree and 0 = bachelor's degree. [i]1 = male and 0 = female. [j]1 = Black. [k]1 = Hispanic. [l]1 = Asian. [m]1 = "other" race/ethnicity. [n]Non-STEM GPA minus STEM GPA. *$p < .05$. **$p < .01$. M = predictor is mediated by undergraduate STEM GPA.

Table 65

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	-0.11	(0.16)	0.89	0.94
Cohort SAT[b]	-0.00	(0.00)	1.00	0.89
Admission rate[c]	0.41	(0.47)	1.50	1.07
Proportion females in STEM[d]	-0.02	(0.11)	0.98	0.98
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.45
SAT tilt[e]	-0.00**	(0.00)	1.00	0.89
High school achievement	0.12**	(0.02)	1.12	1.10
High school STEM coursework	0.21**	(0.02)	1.24	1.20
High school extracurricular activities and awards in STEM	0.15**	(0.01)	1.16	1.16
Self-rated STEM ability	0.49**	(0.03)	1.64	1.39
High school interest in STEM	0.00	(0.04)	1.00	1.00
Degree goal_Graduate degree[f]	0.04	(0.03)	1.04	1.02
Gender_Male[g]	0.53**	(0.06)	1.70	1.30
Race/ethnicity_Black[h]	0.47**	(0.06)	1.61	1.13
Race/ethnicity_Hispanic[i]	0.23**	(0.06)	1.25	1.07
Race/ethnicity_Asian[j]	0.45**	(0.06)	1.57	1.14
Race/ethnicity_Other[k]	0.36**	(0.07)	1.43	1.06
SES	0.00	(0.02)	1.00	1.00
Freshman STEM GPA	0.05	(0.05)	1.05	1.05
Freshman GPA tilt[l]	0.23**	(0.04)	1.26	1.17
Freshman STEM GPA*Gender	0.06	(0.03)	1.06	
Cross-level interaction				
Proportion females in STEM*Gender	-0.22**	(0.07)	0.81	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Freshman STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table 66

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Biological Science Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	-0.33	(0.20)	0.72	0.85
Cohort SAT[b]	0.00	(0.00)	1.00	1.07
Admission rate[c]	0.64	(0.56)	1.91	1.11
Proportion females in STEM[d]	0.30**	(0.09)	1.35	1.35
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.38
SAT tilt[e]	0.00	(0.00)	1.00	1.00
High school achievement	0.10	(0.06)	1.11	1.08
High school STEM coursework	0.08*	(0.03)	1.08	1.07
High school extracurricular activities and awards in STEM	0.05*	(0.02)	1.05	1.05
Self-rated STEM ability	0.20**	(0.06)	1.23	1.13
High school interest in STEM	0.00	(0.02)	1.00	1.00
Degree goal_Graduate degree[f]	0.29**	(0.08)	1.33	1.13
Gender_Male[g]	0.26**	(0.07)	1.29	1.13
Race/ethnicity_Black[h]	0.38**	(0.10)	1.46	1.10
Race/ethnicity_Hispanic[i]	0.13	(0.10)	1.14	1.04
Race/ethnicity_Asian[j]	0.28**	(0.08)	1.33	1.11
Race/ethnicity_Other[k]	0.17	(0.11)	1.18	1.03
SES	0.02	(0.04)	1.02	1.02
Freshman STEM GPA	0.33**	(0.10)	1.39	1.39
Freshman GPA tilt[l]	0.28**	(0.08)	1.33	1.20
Freshman STEM GPA*Gender	0.00	(0.06)	1.00	
Cross-level interaction				
Proportion females in STEM*Gender	-0.17*	(0.08)	0.85	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Freshman STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Freshman non-STEM GPA minus freshman STEM GPA. $*p < .05$. $**p < .01$.

Table 67

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b	(*SE*)	Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	0.00	(0.16)	1.00	1.00
Cohort SAT[b]	-0.00	(0.00)	1.00	0.82
Admission rate[c]	0.53	(0.52)	1.71	1.09
Proportion females in STEM[d]	-0.11	(0.13)	0.90	0.90
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.55
SAT tilt[e]	-0.00**	(0.00)	1.00	0.83
High school achievement	0.11**	(0.03)	1.12	1.10
High school STEM coursework	0.21**	(0.03)	1.23	1.19
High school extracurricular activities and awards in STEM	0.18**	(0.02)	1.20	1.20
Self-rated STEM ability	0.47**	(0.03)	1.60	1.38
High school interest in STEM	0.20**	(0.05)	1.23	1.20
Degree goal_Graduate degree[f]	-0.14**	(0.03)	0.87	0.94
Gender_Male[g]	0.86**	(0.07)	2.35	1.53
Race/ethnicity_Black[h]	0.52**	(0.08)	1.69	1.14
Race/ethnicity_Hispanic[i]	0.27**	(0.07)	1.31	1.08
Race/ethnicity_Asian[j]	0.38**	(0.06)	1.46	1.11
Race/ethnicity_Other[k]	0.33**	(0.08)	1.39	1.05
SES	-0.02	(0.02)	0.98	0.98
Freshman STEM GPA	-0.01	(0.04)	0.99	0.99
Freshman GPA tilt[l]	0.19**	(0.05)	1.21	1.13
Freshman STEM GPA*Gender	0.07*	(0.03)	1.07	
Cross-level interaction				
Proportion females in STEM*Gender	-0.16	(0.10)	0.86	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Freshman STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table 68

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting Male-dominated STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	-0.16	(0.17)	0.86	0.93
Cohort SAT[b]	-0.00	(0.00)	1.00	0.95
Admission rate[c]	0.58	(0.55)	1.78	1.10
Proportion females in STEM[d]	-0.08	(0.14)	0.92	0.92
Individual-level Predictors				
SAT-Math	0.01**	(0.00)	1.01	1.61
SAT tilt[e]	-0.00**	(0.00)	1.00	0.81
High school achievement	0.08**	(0.03)	1.08	1.07
High school STEM coursework (excluding biological sciences)	0.17**	(0.02)	1.19	1.15
High school extracurricular activities and awards in STEM	0.19**	(0.02)	1.21	1.21
Self-rated STEM ability	0.42**	(0.04)	1.52	1.33
High school interest in STEM (excluding biological sciences)	0.34**	(0.05)	1.41	1.37
Degree goal_Graduate degree[f]	-0.26**	(0.04)	0.77	0.88
Gender_Male[g]	1.06**	(0.07)	2.90	1.70
Race/ethnicity_Black[h]	0.49**	(0.09)	1.64	1.13
Race/ethnicity_Hispanic[i]	0.17*	(0.07)	1.19	1.05
Race/ethnicity_Asian[j]	0.13*	(0.06)	1.14	1.04
Race/ethnicity_Other[k]	0.23*	(0.10)	1.26	1.03
SES	-0.05*	(0.02)	0.95	0.96
Freshman STEM GPA	-0.04	(0.04)	0.96	0.96
Freshman GPA tilt[l]	0.06	(0.05)	1.06	1.04
Freshman STEM GPA*Gender	0.03	(0.03)	1.03	
Cross-level interaction				
Proportion females in STEM*Gender	-0.18	(0.11)	0.84	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM fields by the second year of college and 1 = the student remained in a male-dominated STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Freshman STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table 69

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in STEM Fields

	b	(*SE*)	Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	0.40	(0.30)	1.50	1.23
Cohort SAT[b]	-0.00	(0.00)	1.00	0.75
Admission rate[c]	-1.14	(0.89)	0.32	0.83
Proportion females in STEM[d]	-0.20	(0.30)	0.82	0.82
Individual-level Predictors				
SAT-Math	0.00	(0.00)	1.00	1.05
SAT tilt[e]	-0.00**	(0.00)	1.00	0.88
High school achievement	-0.02	(0.05)	0.98	0.99
High school STEM coursework	0.05	(0.05)	1.05	1.05
High school extracurricular activities and awards in STEM	-0.05*	(0.02)	0.95	0.94
Self-rated STEM ability	0.02	(0.06)	1.02	1.01
High school interest in STEM	0.08**	(0.02)	1.08	1.21
Degree goal_Graduate degree[f]	0.11	(0.08)	1.12	1.05
Gender_Male[g]	0.08	(0.12)	1.09	1.04
Race/ethnicity_Black[h]	-0.07	(0.19)	0.93	0.98
Race/ethnicity_Hispanic[i]	-0.16	(0.10)	0.85	0.96
Race/ethnicity_Asian[j]	-0.13	(0.10)	0.88	0.96
Race/ethnicity_Other[k]	0.07	(0.20)	1.08	1.01
SES	-0.04	(0.04)	0.96	0.97
Undergraduate STEM GPA	0.73**	(0.13)	2.08	2.08
Undergraduate GPA tilt[l]	0.35	(0.18)	1.42	1.18
Undergraduate STEM GPA*Gender	0.06	(0.10)	1.06	
Cross-level interaction				
Proportion females in STEM*Gender	-0.38**	(0.14)	0.68	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Undergraduate STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Undergraduate non-STEM GPA minus undergraduate STEM GPA. **p* < .05. ***p* < .01.

Table 70

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	b	(*SE*)	Exp(*b*)	Exp(*b**SDx*)
School-level Predictors				
Public/Private[a]	0.37	(0.37)	1.45	1.21
Cohort SAT[b]	-0.00	(0.00)	1.00	0.93
Admission rate[c]	-2.32*	(1.00)	0.10	0.68
Proportion females in STEM[d]	-0.20	(0.30)	0.82	0.82
Individual-level Predictors				
SAT-Math	0.00	(0.00)	1.00	1.06
SAT tilt[e]	-0.00	(0.00)	1.00	0.90
High school achievement	0.05	(0.12)	1.05	1.04
High school STEM coursework	-0.01	(0.10)	0.99	0.99
High school extracurricular activities and awards in STEM	-0.07	(0.05)	0.93	0.92
Self-rated STEM ability	-0.10	(0.12)	0.90	0.94
High school interest in STEM	0.05	(0.04)	1.06	1.14
Degree goal_Graduate degree[f]	0.32	(0.18)	1.38	1.14
Gender_Male[g]	0.04	(0.17)	1.05	1.02
Race/ethnicity_Black[h]	-0.05	(0.26)	0.96	0.99
Race/ethnicity_Hispanic[i]	-0.21	(0.27)	0.81	0.95
Race/ethnicity_Asian[j]	0.22	(0.17)	1.25	1.09
Race/ethnicity_Other[k]	0.32	(0.53)	1.37	1.06
SES	0.00	(0.08)	1.00	1.00
Undergraduate STEM GPA	0.67**	(0.14)	1.96	1.96
Undergraduate GPA tilt[l]	0.45	(0.23)	1.57	1.21
Undergraduate STEM GPA*Gender	-0.08	(0.14)	0.92	
Cross-level interaction				
Proportion females in STEM*Gender	0.01	(0.20)	1.01	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Undergraduate STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Undergraduate non-STEM GPA minus undergraduate STEM GPA. *$p < .05$. **$p < .01$.

Table 71

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	0.51	(0.30)	1.66	1.29
Cohort SAT[b]	-0.00	(0.00)	1.00	0.70
Admission rate[c]	0.43	(0.98)	1.53	1.07
Proportion females in STEM[d]	-0.02	(0.15)	0.98	0.98
Individual-level Predictors				
SAT-Math	0.00	(0.00)	1.00	1.02
SAT tilt[e]	-0.00*	(0.00)	1.00	0.89
High school achievement	-0.05	(0.06)	0.96	0.97
High school STEM coursework	0.09	(0.05)	1.09	1.09
High school extracurricular activities and awards in STEM	-0.04	(0.03)	0.96	0.95
Self-rated STEM ability	0.08	(0.09)	1.08	1.04
High school interest in STEM	0.08**	(0.02)	1.08	1.20
Degree goal_Graduate degree[f]	0.12	(0.09)	1.13	1.06
Gender_Male[g]	0.15	(0.20)	1.17	1.07
Race/ethnicity_Black[h]	-0.08	(0.23)	0.93	0.98
Race/ethnicity_Hispanic[i]	-0.17	(0.15)	0.85	0.96
Race/ethnicity_Asian[j]	-0.22	(0.11)	0.80	0.93
Race/ethnicity_Other[k]	-0.14	(0.26)	0.87	0.98
SES	-0.05	(0.04)	0.95	0.96
Undergraduate STEM GPA	0.81**	(0.15)	2.25	2.25
Undergraduate GPA tilt[l]	0.34	(0.20)	1.41	1.18
Undergraduate STEM GPA*Gender	0.07	(0.14)	1.07	
Cross-level interaction				
Proportion females in STEM*Gender	-0.37	(0.23)	0.69	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Undergraduate STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Undergraduate non-STEM GPA minus undergraduate STEM GPA. *$p < .05$. **$p < .01$.

Table 72

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting Male-dominated STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	0.55	(0.32)	1.73	1.32
Cohort SAT[b]	-0.00	(0.00)	1.00	0.71
Admission rate[c]	-0.10	(0.91)	0.90	0.98
Proportion females in STEM[d]	0.06	(0.14)	1.06	1.06
Individual-level Predictors				
SAT-Math	0.00	(0.00)	1.00	1.06
SAT tilt[e]	-0.00**	(0.00)	1.00	0.86
High school achievement	-0.08	(0.05)	0.92	0.94
High school STEM coursework (excluding biological sciences)	0.08	(0.05)	1.09	1.09
High school extracurricular activities and awards in STEM	-0.05*	(0.02)	0.95	0.94
Self-rated STEM ability	0.05	(0.07)	1.06	1.03
High school interest in STEM (excluding biological sciences)	0.09**	(0.02)	1.10	1.24
Degree goal_Graduate degree[f]	0.04	(0.08)	1.04	1.02
Gender_Male[g]	0.04	(0.19)	1.04	1.02
Race/ethnicity_Black[h]	-0.08	(0.21)	0.92	0.98
Race/ethnicity_Hispanic[i]	-0.11	(0.14)	0.90	0.98
Race/ethnicity_Asian[j]	-0.27*	(0.12)	0.76	0.91
Race/ethnicity_Other[k]	-0.20	(0.24)	0.82	0.97
SES	-0.04	(0.03)	0.96	0.97
Undergraduate STEM GPA	0.79**	(0.16)	2.20	2.20
Undergraduate GPA tilt[l]	0.35	(0.20)	1.41	1.18
Undergraduate STEM GPA*Gender	0.02	(0.13)	1.02	
Cross-level interaction				
Proportion females in STEM*Gender	-0.78**	(0.28)	0.46	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM majors between the second and fourth years of college and 1 = the student remained in a male-dominated STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Undergraduate STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Undergraduate non-STEM GPA minus undergraduate STEM GPA. *$p < .05$. **$p < .01$.

Table 73

Survival Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence in Multiple-year Longitudinal Sample

	b	(*SE*)	Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	-0.44	(0.36)	0.65	0.80
Cohort SAT[b]	-0.00	(0.00)	1.00	0.93
Admission rate[c]	-0.17	(0.85)	0.84	0.98
Proportion females in STEM[d]	0.25	(0.15)	1.29	1.29
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.42
SAT tilt[e]	-0.00**	(0.00)	1.00	0.88
High school achievement	0.10*	(0.05)	1.11	1.07
High school STEM coursework	0.06**	(0.02)	1.06	1.06
High school extracurricular activities and awards in STEM	0.08**	(0.02)	1.08	1.10
Self-rated STEM ability	0.17**	(0.05)	1.19	1.10
High school interest in STEM	0.55**	(0.07)	1.74	1.45
Degree goal_Graduate degree[f]	0.15**	(0.05)	1.16	1.07
Gender_Male[g]	0.20*	(0.10)	1.22	1.10
Race/ethnicity_Black[h]	0.38**	(0.08)	1.46	1.10
Race/ethnicity_Hispanic[i]	-0.01	(0.09)	0.99	1.00
Race/ethnicity_Asian[j]	0.23**	(0.08)	1.25	1.08
Race/ethnicity_Other[k]	0.33*	(0.15)	1.38	1.05
SES	0.02	(0.04)	1.02	1.02
Cumulative STEM GPA	0.30**	(0.05)	1.35	1.35
Cumulative GPA tilt[l]	0.37**	(0.03)	1.45	1.27
Time	-0.14**	(0.04)	0.87	0.89
Cumulative STEM GPA*Gender	0.07	(0.04)	1.07	
Cross-level interaction				
Proportion females in STEM*Gender	-0.58**	(0.15)	0.56	

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field and 1 = the student remained in a STEM field. *b* = unstandardized coefficient. Exp(*b*) = exponentiation of unstandardized coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized coefficient (standardized odds ratio). Cumulative STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Cumulative non-STEM GPA minus cumulative STEM GPA. *$p < .05$. **$p < .01$.

Table 74

Survival Analysis using all School-level and Individual-level Predictors and Time Interactions: Predicting STEM Persistence in Multiple-year Longitudinal Sample

	b	(*SE*)	Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	-0.45	(0.36)	0.64	0.80
Cohort SAT[b]	-0.00	(0.00)	1.00	0.93
Admission rate[c]	-0.18	(1.07)	0.83	0.97
Proportion females in STEM[d]	-0.11	(0.22)	0.90	0.90
Public/Private*Time	0.14	(0.08)	1.15	
Cohort SAT*Time	0.00	(0.00)	1.00	
Admission rate*Time	-0.52**	(0.19)	0.59	
Proportion females in STEM*Time	-0.04	(0.07)	0.96	
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.42
SAT tilt[e]	-0.00**	(0.00)	1.00	0.88
High school achievement	0.10	(0.07)	1.10	1.07
High school STEM coursework	0.06	(0.04)	1.06	1.06
High school extracurricular activities and awards in STEM	0.08*	(0.03)	1.08	1.10
Self-rated STEM ability	0.17*	(0.09)	1.19	1.10
High school interest in STEM	0.55**	(0.06)	1.74	1.45
Degree goal_Graduate degree[f]	0.15	(0.08)	1.16	1.07
Gender_Male[g]	0.21	(0.15)	1.24	1.11
Race/ethnicity_Black[h]	0.38*	(0.16)	1.47	1.10
Race/ethnicity_Hispanic[i]	-0.01	(0.15)	0.99	1.00
Race/ethnicity_Asian[j]	0.22	(0.12)	1.25	1.08
Race/ethnicity_Other[k]	0.32	(0.24)	1.38	1.05
SES	0.02	(0.05)	1.02	1.02
Cumulative STEM GPA	0.26**	(0.06)	1.30	1.30
Cumulative GPA tilt[l]	0.15**	(0.05)	1.16	1.16
Time	-0.12**	(0.04)	0.88	0.90
Cumulative STEM GPA*Gender	0.09	(0.08)	1.09	
SAT-Math*Time	0.00	(0.00)	1.00	
SAT tilt*Time	0.00	(0.00)	1.00	
High school achievement*Time	-0.03	(0.04)	0.97	
High school STEM coursework*Time	0.01	(0.02)	1.01	
High school extracurricular activities and awards in STEM*Time	-0.03	(0.02)	0.97	
Self-rated STEM ability*Time	0.02	(0.05)	1.02	
High school interest in STEM*Time	-0.03	(0.04)	0.97	
Degree goal_Graduate degree*Time	0.01	(0.05)	1.01	
Gender_Male*Time	0.05	(0.08)	1.06	
Race/ethnicity_Black*Time	0.02	(0.10)	1.02	
Race/ethnicity_Hispanic*Time	0.03	(0.09)	1.03	
Race/ethnicity_Asian*Time	0.00	(0.07)	1.00	
Race/ethnicity_Other*Time	0.09	(0.15)	1.09	
SES*Time	-0.01	(0.03)	0.99	
Cumulative STEM GPA*Time	0.11**	(0.04)	1.11	
Cumulative GPA tilt*Time	0.09*	(0.03)	1.09	

(*Table 74 continues*)

(*Table 74 continued*)

	b (*SE*)		Exp(*b*)	Exp(*b**SDx*)
Cumulative STEM GPA*Gender*Time	-0.03	(0.05)	0.97	
Cross-level interaction				
Proportion females in STEM*Gender	-0.58**	(0.19)	0.56	
Proportion females in STEM*Gender*Time	0.05	(0.09)	1.05	

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field and 1 = the student remained in a STEM field. *b* = unstandardized coefficient. Exp(*b*) = exponentiation of unstandardized coefficient (odds ratio). Exp(*b**SDx*) = exponentiation of standardized coefficient (standardized odds ratio). All predictors were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Cumulative non-STEM GPA minus cumulative STEM GPA. *p < .05. **p < .01.

Table 75

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	-0.12	(0.16)	0.89	0.94
Cohort SAT[b]	-0.00	(0.00)	1.00	0.89
Admission rate[c]	0.41	(0.48)	1.51	1.07
Proportion females in STEM[d]	-0.03	(0.11)	0.97	0.97
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.46
SAT tilt[e]	-0.00**	(0.00)	1.00	0.91
High school achievement	0.13**	(0.02)	1.14	1.11
High school STEM coursework	0.21**	(0.02)	1.24	1.20
High school extracurricular activities and awards in STEM	0.15**	(0.01)	1.16	1.17
Self-rated STEM ability	0.49**	(0.03)	1.63	1.39
High school interest in STEM	-0.01	(0.04)	0.99	0.99
Degree goal_Graduate degree[f]	0.05	(0.03)	1.05	1.02
Gender_Male[g]	0.52**	(0.06)	1.69	1.30
Race/ethnicity_Black[h]	0.47**	(0.06)	1.60	1.13
Race/ethnicity_Hispanic[i]	0.23**	(0.05)	1.26	1.07
Race/ethnicity_Asian[j]	0.45**	(0.06)	1.56	1.14
Race/ethnicity_Other[k]	0.36**	(0.07)	1.44	1.06
SES	0.00	(0.02)	1.00	1.00
Cross-level interaction				
Proportion females in STEM*Gender	-0.21**	(0.07)	0.81	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 76

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Biological Science Fields

	b	(*SE*)	Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	-0.30	(0.20)	0.74	0.86
Cohort SAT[b]	0.00	(0.00)	1.00	1.01
Admission rate[c]	0.60	(0.57)	1.82	1.10
Proportion females in STEM[d]	0.29**	(0.09)	1.34	1.34
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.49
SAT tilt[e]	0.00	(0.00)	1.00	1.03
High school achievement	0.20**	(0.05)	1.23	1.15
High school STEM coursework	0.08*	(0.03)	1.08	1.07
High school extracurricular activities and awards in STEM	0.05	(0.02)	1.05	1.05
Self-rated STEM ability	0.20**	(0.06)	1.23	1.13
High school interest in STEM	0.00	(0.02)	1.00	1.00
Degree goal_Graduate degree[f]	0.28**	(0.07)	1.32	1.12
Gender_Male[g]	0.22**	(0.07)	1.24	1.11
Race/ethnicity_Black[h]	0.35**	(0.10)	1.42	1.09
Race/ethnicity_Hispanic[i]	0.11	(0.10)	1.12	1.03
Race/ethnicity_Asian[j]	0.29**	(0.09)	1.33	1.11
Race/ethnicity_Other[k]	0.17	(0.11)	1.19	1.03
SES	0.04	(0.04)	1.04	1.03
Cross-level interaction				
Proportion females in STEM*Gender	-0.16*	(0.07)	0.85	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 77

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	0.00	(0.16)	1.00	1.00
Cohort SAT[b]	-0.00	(0.00)	1.00	0.83
Admission rate[c]	0.54	(0.52)	1.72	1.09
Proportion females in STEM[d]	-0.12	(0.13)	0.89	0.89
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.53
SAT tilt[e]	-0.00**	(0.00)	1.00	0.85
High school achievement	0.11**	(0.03)	1.12	1.10
High school STEM coursework	0.21**	(0.03)	1.24	1.19
High school extracurricular activities and awards in STEM	0.18**	(0.02)	1.20	1.20
Self-rated STEM ability	0.47**	(0.03)	1.60	1.38
High school interest in STEM	0.20**	(0.05)	1.22	1.20
Degree goal_Graduate degree[f]	-0.13**	(0.03)	0.88	0.94
Gender_Male[g]	0.86**	(0.07)	2.37	1.54
Race/ethnicity_Black[h]	0.53**	(0.08)	1.70	1.14
Race/ethnicity_Hispanic[i]	0.28**	(0.06)	1.32	1.08
Race/ethnicity_Asian[j]	0.37**	(0.07)	1.45	1.11
Race/ethnicity_Other[k]	0.33**	(0.08)	1.39	1.05
SES	-0.02	(0.02)	0.98	0.98
Cross-level interaction				
Proportion females in STEM*Gender	-0.15	(0.11)	0.86	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 78

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Male-dominated STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	-0.16	(0.17)	0.85	0.92
Cohort SAT[b]	-0.00	(0.00)	1.00	0.96
Admission rate[c]	0.59	(0.55)	1.80	1.10
Proportion females in STEM[d]	-0.08	(0.14)	0.92	0.92
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.59
SAT tilt[e]	-0.00**	(0.00)	1.00	0.81
High school achievement	0.07*	(0.03)	1.07	1.06
High school STEM coursework (excluding biological sciences)	0.17**	(0.02)	1.19	1.15
High school extracurricular activities and awards in STEM	0.19**	(0.02)	1.21	1.21
Self-rated STEM ability	0.42**	(0.04)	1.52	1.33
High school interest in STEM (excluding biological sciences)	0.34**	(0.05)	1.40	1.37
Degree goal_Graduate degree[f]	-0.26**	(0.04)	0.77	0.88
Gender_Male[g]	1.07**	(0.07)	2.93	1.71
Race/ethnicity_Black[h]	0.50**	(0.09)	1.65	1.13
Race/ethnicity_Hispanic[i]	0.18*	(0.07)	1.19	1.05
Race/ethnicity_Asian[j]	0.13*	(0.06)	1.14	1.04
Race/ethnicity_Other[k]	0.23*	(0.10)	1.26	1.03
SES	-0.05*	(0.02)	0.95	0.96
Cross-level interaction				
Proportion females in STEM*Gender	-0.18	(0.11)	0.84	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM fields by the second year of college and 1 = the student remained in a male-dominated STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 79

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	0.52	(0.29)	1.68	1.30
Cohort SAT[b]	-0.00*	(0.00)	1.00	0.70
Admission rate[c]	-1.09	(0.85)	0.33	0.83
Proportion females in STEM[d]	-0.18	(0.29)	0.84	0.84
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.24
SAT tilt[e]	-0.00	(0.00)	1.00	0.94
High school achievement	0.22**	(0.06)	1.25	1.16
High school STEM coursework	0.06	(0.05)	1.06	1.06
High school extracurricular activities and awards in STEM	-0.05	(0.03)	0.95	0.94
Self-rated STEM ability	0.02	(0.07)	1.02	1.01
High school interest in STEM	0.07**	(0.01)	1.07	1.19
Degree goal_Graduate degree[f]	0.09	(0.08)	1.09	1.04
Gender_Male[g]	0.00	(0.12)	1.00	1.00
Race/ethnicity_Black[h]	-0.21	(0.17)	0.81	0.96
Race/ethnicity_Hispanic[i]	-0.23*	(0.10)	0.79	0.95
Race/ethnicity_Asian[j]	-0.12	(0.09)	0.89	0.96
Race/ethnicity_Other[k]	0.00	(0.19)	1.00	1.00
SES	-0.01	(0.04)	0.99	0.99
Cross-level interaction				
Proportion females in STEM*Gender	-0.38**	(0.15)	0.68	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 80

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	0.52	(0.35)	1.68	1.30
Cohort SAT[b]	-0.00	(0.00)	1.00	0.87
Admission rate[c]	-2.33*	(1.00)	0.10	0.68
Proportion females in STEM[d]	-0.21	(0.30)	0.81	0.81
Individual-level Predictors				
SAT-Math	0.00*	(0.00)	1.00	1.24
SAT tilt[e]	-0.00	(0.00)	1.00	0.96
High school achievement	0.24*	(0.11)	1.27	1.17
High school STEM coursework	-0.02	(0.09)	0.99	0.99
High school extracurricular activities and awards in STEM	-0.09	(0.05)	0.92	0.91
Self-rated STEM ability	-0.08	(0.13)	0.92	0.95
High school interest in STEM	0.04	(0.04)	1.05	1.11
Degree goal_Graduate degree[f]	0.30	(0.17)	1.36	1.13
Gender_Male[g]	-0.02	(0.16)	0.98	0.99
Race/ethnicity_Black[h]	-0.14	(0.26)	0.87	0.97
Race/ethnicity_Hispanic[i]	-0.30	(0.23)	0.74	0.93
Race/ethnicity_Asian[j]	0.22	(0.17)	1.24	1.09
Race/ethnicity_Other[k]	0.24	(0.56)	1.28	1.05
SES	0.03	(0.08)	1.03	1.03
Cross-level interaction				
Proportion females in STEM*Gender	-0.04	(0.20)	0.96	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 81

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	0.57	(0.29)	1.76	1.33
Cohort SAT[b]	-0.00*	(0.00)	1.00	0.66
Admission rate[c]	0.42	(0.85)	1.52	1.07
Proportion females in STEM[d]	0.01	(0.14)	1.01	1.01
Individual-level Predictors				
SAT-Math	0.00*	(0.00)	1.00	1.22
SAT tilt[e]	-0.00	(0.00)	1.00	0.95
High school achievement	0.23**	(0.06)	1.26	1.17
High school STEM coursework	0.10*	(0.05)	1.11	1.12
High school extracurricular activities and awards in STEM	-0.03	(0.03)	0.97	0.96
Self-rated STEM ability	0.07	(0.09)	1.07	1.04
High school interest in STEM	0.07**	(0.02)	1.08	1.18
Degree goal_Graduate degree[f]	0.08	(0.08)	1.09	1.04
Gender_Male[g]	0.00	(0.20)	1.00	1.00
Race/ethnicity_Black[h]	-0.25	(0.22)	0.78	0.95
Race/ethnicity_Hispanic[i]	-0.21	(0.18)	0.81	0.95
Race/ethnicity_Asian[j]	-0.23**	(0.08)	0.79	0.93
Race/ethnicity_Other[k]	-0.20	(0.26)	0.82	0.97
SES	-0.03	(0.04)	0.97	0.98
Cross-level interaction				
Proportion females in STEM*Gender	-0.42	(0.22)	0.66	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM major for a non-STEM major between the second and fourth years of college and 1 = the student remained in a STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 82

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Male-dominated STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	0.61	(0.31)	1.85	1.37
Cohort SAT[b]	-0.00*	(0.00)	1.00	0.68
Admission rate[c]	-0.08	(0.81)	0.93	0.99
Proportion females in STEM[d]	0.08	(0.13)	1.09	1.09
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.24
SAT tilt[e]	-0.00	(0.00)	1.00	0.92
High school achievement	0.17**	(0.06)	1.19	1.13
High school STEM coursework (excluding biological sciences)	0.10*	(0.05)	1.11	1.11
High school extracurricular activities and awards in STEM	-0.04	(0.02)	0.96	0.95
Self-rated STEM ability	0.05	(0.07)	1.05	1.03
High school interest in STEM (excluding biological sciences)	0.09**	(0.01)	1.09	1.23
Degree goal_Graduate degree[f]	0.00	(0.07)	1.00	1.00
Gender_Male[g]	-0.09	(0.19)	0.92	0.96
Race/ethnicity_Black[h]	-0.25	(0.20)	0.78	0.95
Race/ethnicity_Hispanic[i]	-0.15	(0.17)	0.86	0.97
Race/ethnicity_Asian[j]	-0.29**	(0.09)	0.75	0.91
Race/ethnicity_Other[k]	-0.26	(0.24)	0.77	0.96
SES	-0.02	(0.04)	0.98	0.98
Cross-level interaction				
Proportion females in STEM*Gender	-0.82**	(0.28)	0.44	

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left male-dominated STEM majors between the second and fourth years of college and 1 = the student remained in a male-dominated STEM major between the second and fourth years of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 83

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.10*	(0.04)	0.06
Cohort SAT[b]	-0.00**	(0.00)	-0.27
Admission rate[c]	-0.21*	(0.10)	-0.04
Proportion females in STEM[d]	0.03	(0.02)	0.03
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.35
SAT tilt[e]	0.00**	(0.00)	0.09
High school achievement	0.30**	(0.01)	0.30
High school STEM coursework	0.01*	(0.01)	0.01
High school extracurricular activities and awards in STEM	-0.02**	(0.00)	-0.02
Self-rated STEM ability	-0.01	(0.01)	-0.01
High school interest in STEM	0.02**	(0.00)	0.02
Degree goal_Graduate degree[f]	-0.04**	(0.01)	-0.02
Gender_Male[g]	-0.13**	(0.01)	-0.08
Race/ethnicity_Black[h]	-0.15**	(0.03)	-0.05
Race/ethnicity_Hispanic[i]	-0.08**	(0.02)	-0.03
Race/ethnicity_Asian[j]	-0.01	(0.02)	-0.00
Race/ethnicity_Other[k]	-0.03	(0.03)	-0.01
SES	0.04**	(0.01)	0.04
Cross-level interaction			
Proportion females in STEM*Gender	-0.01	(0.02)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table 84

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in Biological Science Fields

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.08*	(0.04)	0.05
Cohort SAT[b]	-0.00**	(0.00)	-0.27
Admission rate[c]	-0.15	(0.10)	-0.03
Proportion females in STEM[d]	0.03	(0.02)	0.04
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.36
SAT tilt[e]	0.00**	(0.00)	0.08
High school achievement	0.34**	(0.01)	0.30
High school STEM coursework	0.01	(0.01)	0.01
High school extracurricular activities and awards in STEM	-0.01	(0.01)	-0.01
Self-rated STEM ability	0.03	(0.02)	0.02
High school interest in STEM	0.00	(0.01)	0.00
Degree goal_Graduate degree[f]	-0.06**	(0.02)	-0.03
Gender_Male[g]	-0.08**	(0.03)	-0.05
Race/ethnicity_Black[h]	-0.07	(0.04)	-0.02
Race/ethnicity_Hispanic[i]	-0.10**	(0.02)	-0.03
Race/ethnicity_Asian[j]	0.05*	(0.02)	0.02
Race/ethnicity_Other[k]	0.00	(0.04)	0.00
SES	0.06**	(0.01)	0.06
Cross-level interaction			
Proportion females in STEM*Gender	-0.01	(0.03)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 85

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in Male-dominated STEM Fields (with Predictors Reflecting all STEM Fields)

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.10*	(0.04)	0.06
Cohort SAT[b]	-0.00**	(0.00)	-0.26
Admission rate[c]	-0.19	(0.10)	-0.04
Proportion females in STEM[d]	0.03	(0.02)	0.03
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.34
SAT tilt[e]	0.00**	(0.00)	0.09
High school achievement	0.30**	(0.01)	0.30
High school STEM coursework	0.02**	(0.01)	0.02
High school extracurricular activities and awards in STEM	-0.02**	(0.00)	-0.02
Self-rated STEM ability	-0.01	(0.01)	-0.00
High school interest in STEM	0.01**	(0.00)	0.02
Degree goal_Graduate degree[f]	-0.03**	(0.01)	-0.02
Gender_Male[g]	-0.15**	(0.02)	-0.09
Race/ethnicity_Black[h]	-0.17**	(0.03)	-0.05
Race/ethnicity_Hispanic[i]	-0.07**	(0.02)	-0.02
Race/ethnicity_Asian[j]	-0.02	(0.02)	-0.01
Race/ethnicity_Other[k]	-0.03	(0.03)	-0.00
SES	0.03**	(0.01)	0.03
Cross-level interaction			
Proportion females in STEM*Gender	0.00	(0.02)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *p < .05. **p < .01.

Table 86

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in Male-dominated STEM Fields (with Predictors Reflecting Male-dominated STEM Fields)

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.11**	(0.04)	0.07
Cohort SAT[b]	-0.00**	(0.00)	-0.27
Admission rate[c]	-0.21*	(0.10)	-0.04
Proportion females in STEM[d]	0.00	(0.02)	0.00
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.34
SAT tilt[e]	0.00**	(0.00)	0.09
High school achievement	0.30**	(0.01)	0.30
High school STEM coursework (excluding biological sciences)	0.02**	(0.01)	0.02
High school extracurricular activities and awards in STEM	-0.02**	(0.00)	-0.02
Self-rated STEM ability	-0.01	(0.01)	-0.00
High school interest in STEM (excluding biological sciences)	0.02**	(0.00)	0.02
Degree goal_Graduate degree[f]	-0.03**	(0.01)	-0.02
Gender_Male[g]	-0.14**	(0.01)	-0.09
Race/ethnicity_Black[h]	-0.17**	(0.03)	-0.05
Race/ethnicity_Hispanic[i]	-0.07**	(0.02)	-0.02
Race/ethnicity_Asian[j]	-0.02	(0.02)	-0.01
Race/ethnicity_Other[k]	-0.03	(0.03)	-0.00
SES	0.03**	(0.01)	0.03
Cross-level interaction			
Proportion females in STEM*Gender	0.02	(0.02)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 87

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in STEM Fields

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.15**	(0.05)	0.12
Cohort SAT[b]	-0.00**	(0.00)	-0.15
Admission rate[c]	0.00	(0.09)	0.00
Proportion females in STEM[d]	0.05*	(0.02)	0.08
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.32
SAT tilt[e]	0.00**	(0.00)	0.08
High school achievement	0.29**	(0.02)	0.30
High school STEM coursework	0.01	(0.01)	0.02
High school extracurricular activities and awards in STEM	0.00	(0.01)	0.00
Self-rated STEM ability	0.03	(0.02)	0.02
High school interest in STEM	-0.01*	(0.00)	-0.02
Degree goal_Graduate degree[f]	-0.03	(0.02)	-0.02
Gender_Male[g]	-0.06*	(0.03)	-0.05
Race/ethnicity_Black[h]	-0.20**	(0.04)	-0.07
Race/ethnicity_Hispanic[i]	-0.12**	(0.03)	-0.04
Race/ethnicity_Asian[j]	-0.01	(0.04)	-0.00
Race/ethnicity_Other[k]	-0.06	(0.04)	-0.01
SES	0.03**	(0.01)	0.03
Cross-level interaction			
Proportion females in STEM*Gender	-0.01	(0.03)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 88

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in Biological Science Fields

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.22**	(0.04)	0.18
Cohort SAT[b]	-0.00**	(0.00)	-0.17
Admission rate[c]	-0.04	(0.12)	-0.01
Proportion females in STEM[d]	0.02	(0.01)	0.03
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.38
SAT tilt[e]	0.00**	(0.00)	0.09
High school achievement	0.29**	(0.03)	0.30
High school STEM coursework	-0.01	(0.01)	-0.01
High school extracurricular activities and awards in STEM	-0.02**	(0.01)	-0.04
Self-rated STEM ability	0.04	(0.04)	0.04
High school interest in STEM	-0.01	(0.00)	-0.02
Degree goal_Graduate degree[f]	-0.01	(0.02)	-0.01
Gender_Male[g]	-0.01	(0.03)	-0.01
Race/ethnicity_Black[h]	-0.16**	(0.05)	-0.06
Race/ethnicity_Hispanic[i]	-0.21**	(0.04)	-0.08
Race/ethnicity_Asian[j]	-0.01	(0.03)	-0.01
Race/ethnicity_Other[k]	-0.12*	(0.06)	-0.04
SES	0.04**	(0.01)	0.05
Cross-level interaction			
Proportion females in STEM*Gender	-0.06	(0.04)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 89

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields (with Predictors Reflecting all STEM Fields)

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.10	(0.07)	0.08
Cohort SAT[b]	-0.00	(0.00)	-0.13
Admission rate[c]	0.02	(0.12)	0.01
Proportion females in STEM[d]	0.06	(0.03)	0.10
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.30
SAT tilt[e]	0.00**	(0.00)	0.07
High school achievement	0.28**	(0.02)	0.30
High school STEM coursework	0.02	(0.01)	0.03
High school extracurricular activities and awards in STEM	0.01	(0.01)	0.02
Self-rated STEM ability	0.02	(0.02)	0.02
High school interest in STEM	0.00	(0.00)	0.00
Degree goal_Graduate degree[f]	-0.04*	(0.02)	-0.03
Gender_Male[g]	-0.12**	(0.03)	-0.08
Race/ethnicity_Black[h]	-0.21**	(0.06)	-0.07
Race/ethnicity_Hispanic[i]	-0.08	(0.04)	-0.03
Race/ethnicity_Asian[j]	-0.03	(0.05)	-0.01
Race/ethnicity_Other[k]	-0.03	(0.05)	-0.01
SES	0.02	(0.01)	0.02
Cross-level interaction			
Proportion females in STEM*Gender	-0.07	(0.04)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table 90

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Undergraduate STEM GPA in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields (with Predictors Reflecting Male-dominated STEM Fields)

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.10	(0.08)	0.07
Cohort SAT[b]	-0.00	(0.00)	-0.13
Admission rate[c]	0.02	(0.13)	0.01
Proportion females in STEM[d]	0.06	(0.03)	0.10
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.30
SAT tilt[e]	0.00**	(0.00)	0.07
High school achievement	0.28**	(0.02)	0.30
High school STEM coursework (excluding biological sciences)	0.02*	(0.01)	0.03
High school extracurricular activities and awards in STEM	0.01	(0.01)	0.02
Self-rated STEM ability	0.02	(0.02)	0.02
High school interest in STEM (excluding biological sciences)	0.00	(0.00)	0.00
Degree goal_Graduate degree[f]	-0.04*	(0.02)	-0.03
Gender_Male[g]	-0.10**	(0.03)	-0.06
Race/ethnicity_Black[h]	-0.21**	(0.06)	-0.07
Race/ethnicity_Hispanic[i]	-0.08	(0.04)	-0.03
Race/ethnicity_Asian[j]	-0.03	(0.05)	-0.01
Race/ethnicity_Other[k]	-0.03	(0.05)	-0.01
SES	0.02	(0.01)	0.02
Cross-level interaction			
Proportion females in STEM*Gender	-0.05	(0.07)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is undergraduate STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. $^*p < .05$. $^{**}p < .01$.

Table 91

Summary Table: Gender Differences in Persistence Explained by Individual-level Predictors in All Samples

	HS – STEM[a]	HS – Biological Sciences[a]	HS – Male-dominated STEM[a]	HS – Male-dominated STEM[b]	Year 2 – STEM[a]	Year 2 – Biological Sciences[a]	Year 2 – Male-dominated STEM[a]	Year 2 – Male-dominated STEM[b]	Multiple-year Longitudinal[c]
Baseline gender odds ratio	3.10	1.62	4.77	6.20	1.43	1.02	1.69	1.47	2.07
Gender odds ratio in multivariate model	1.96**	1.43**	2.61**	3.20**	1.39**	1.04	1.52**	1.66**	1.73**

Note. Baseline gender odds ratio is the odds of persistence for males to the odds of persistence for females in each sample. *Gender odds ratio in multivariate model* is the gender coefficient in the multivariate model including all individual-level predictors and indicates the gender differences in persistence that remain after accounting for all other individual-level predictors. [a]The outcome is persistence in any STEM field, and all predictors include all STEM fields. [b]The outcome is persistence in male-dominated STEM fields, and high school STEM coursework and interest exclude biological sciences. [c]The baseline odds ratio is based on persistence through the fourth year of college. **Gender differences remained significant ($p < .01$) in multivariate model.

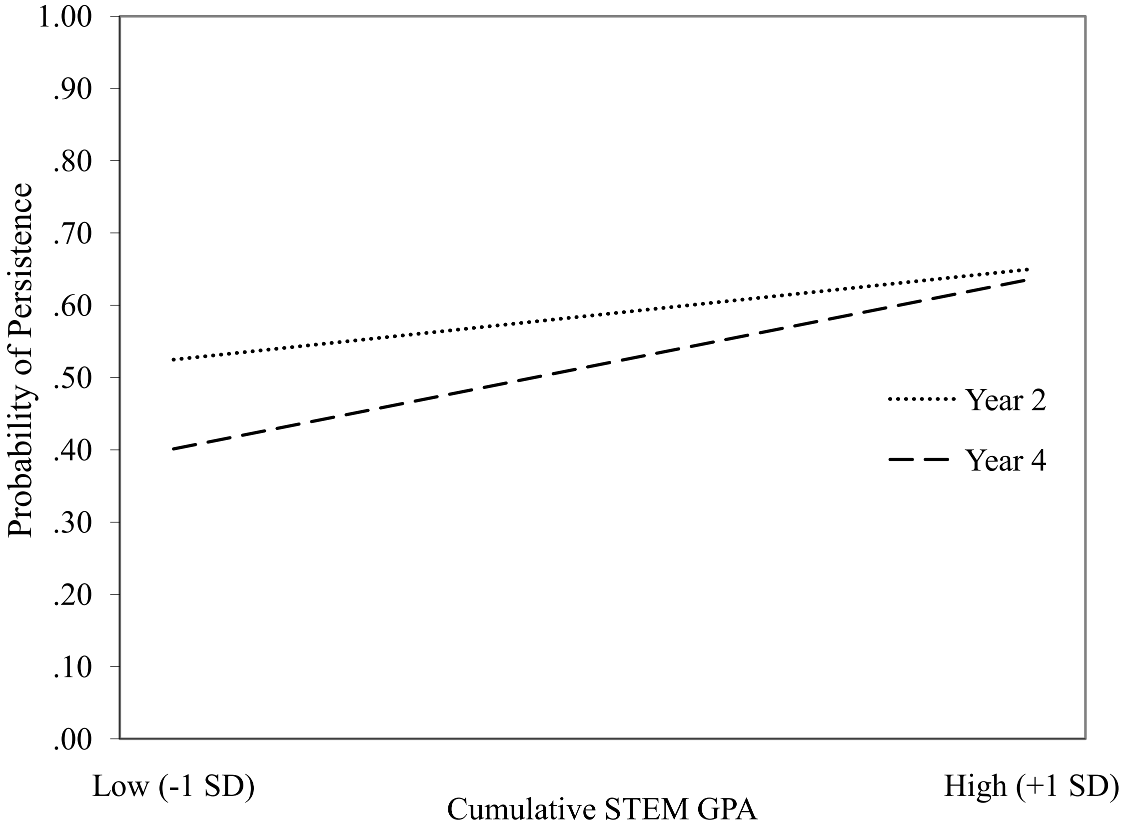

Figure 1. Interaction between Cumulative STEM GPA and Time in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all Individual-level Predictors and Time Interactions).

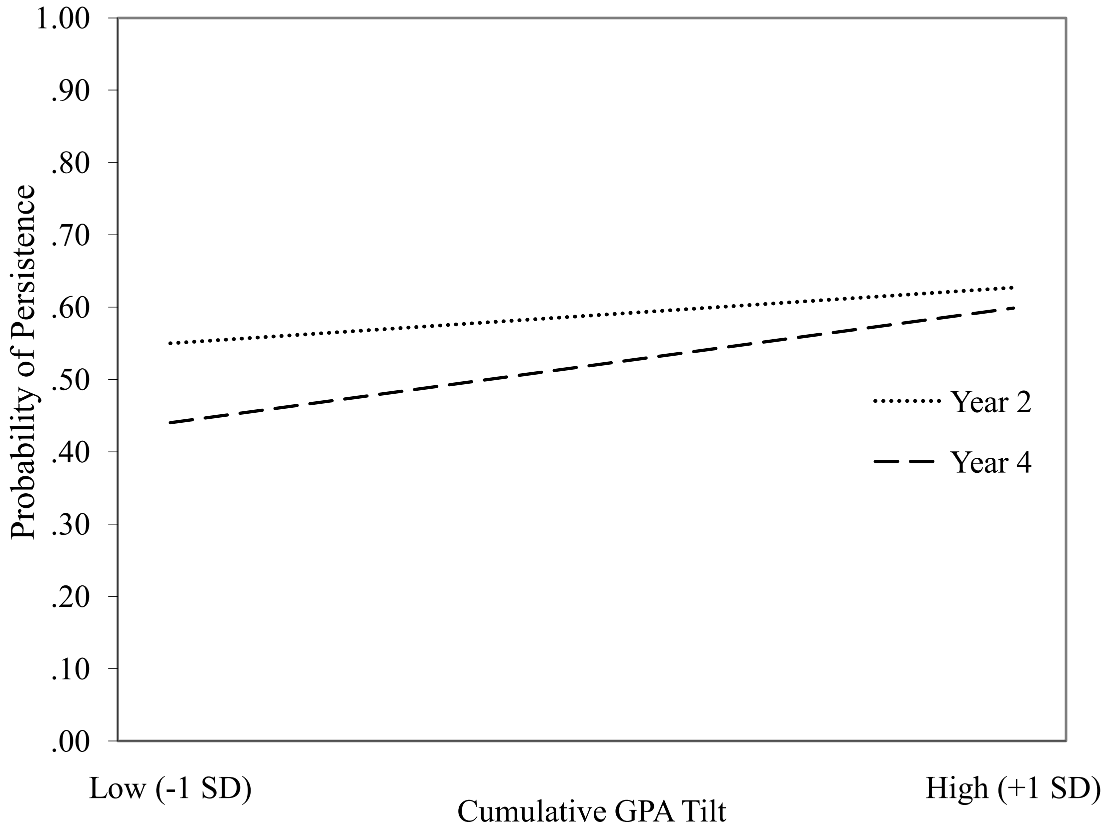

Figure 2. Interaction between Cumulative GPA Tilt and Time in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all Individual-level Predictors and Time Interactions

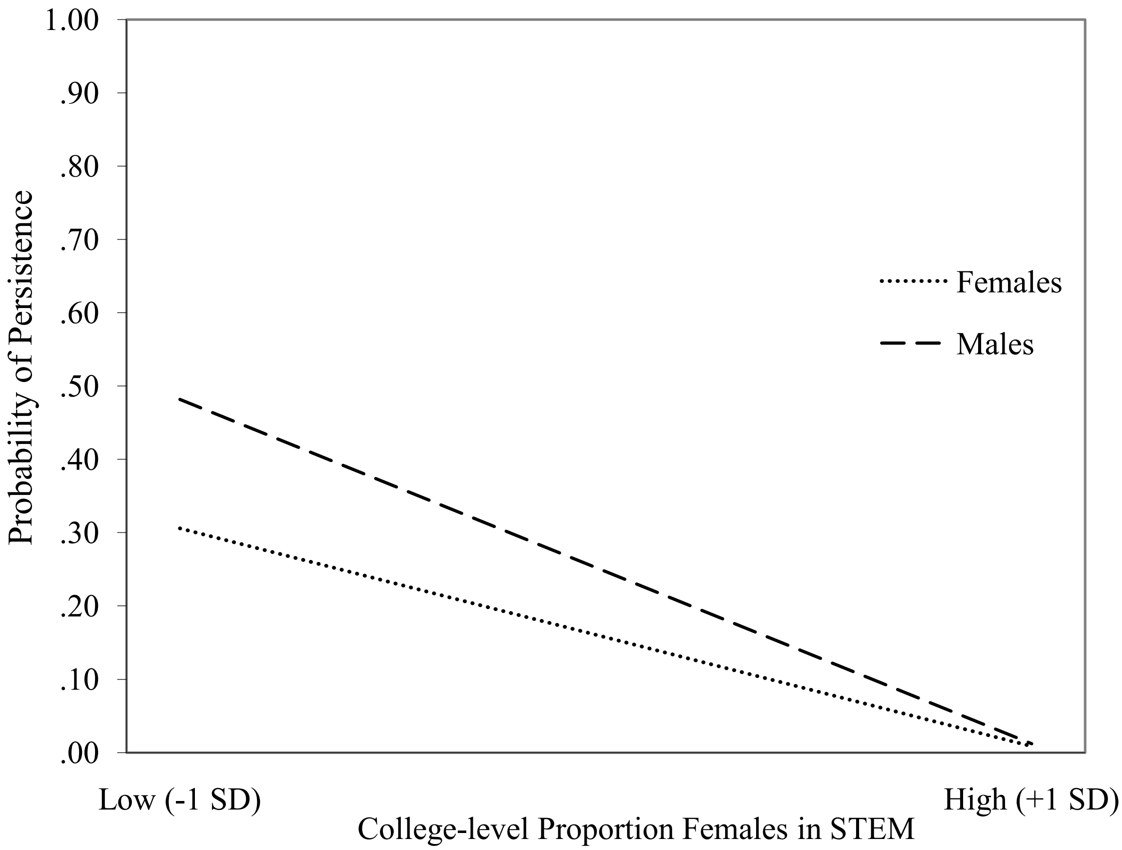

Figure 3. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

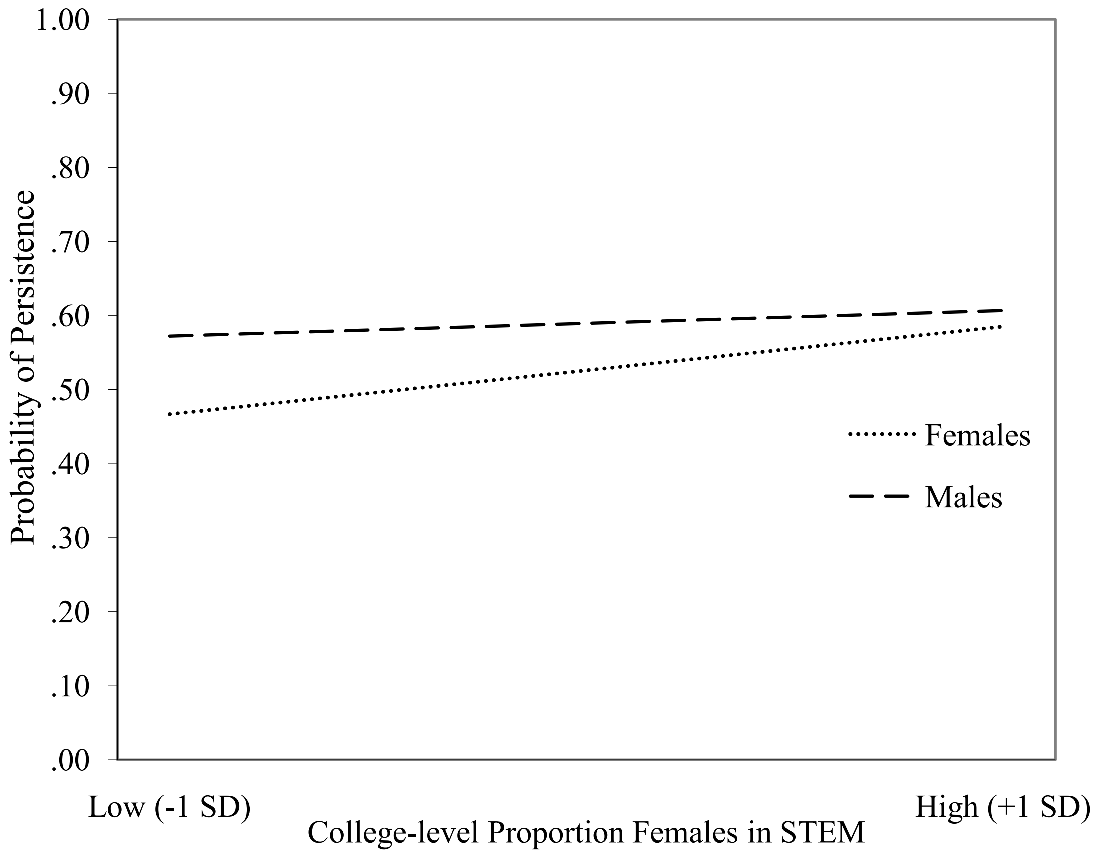

Figure 4. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Biological Science Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

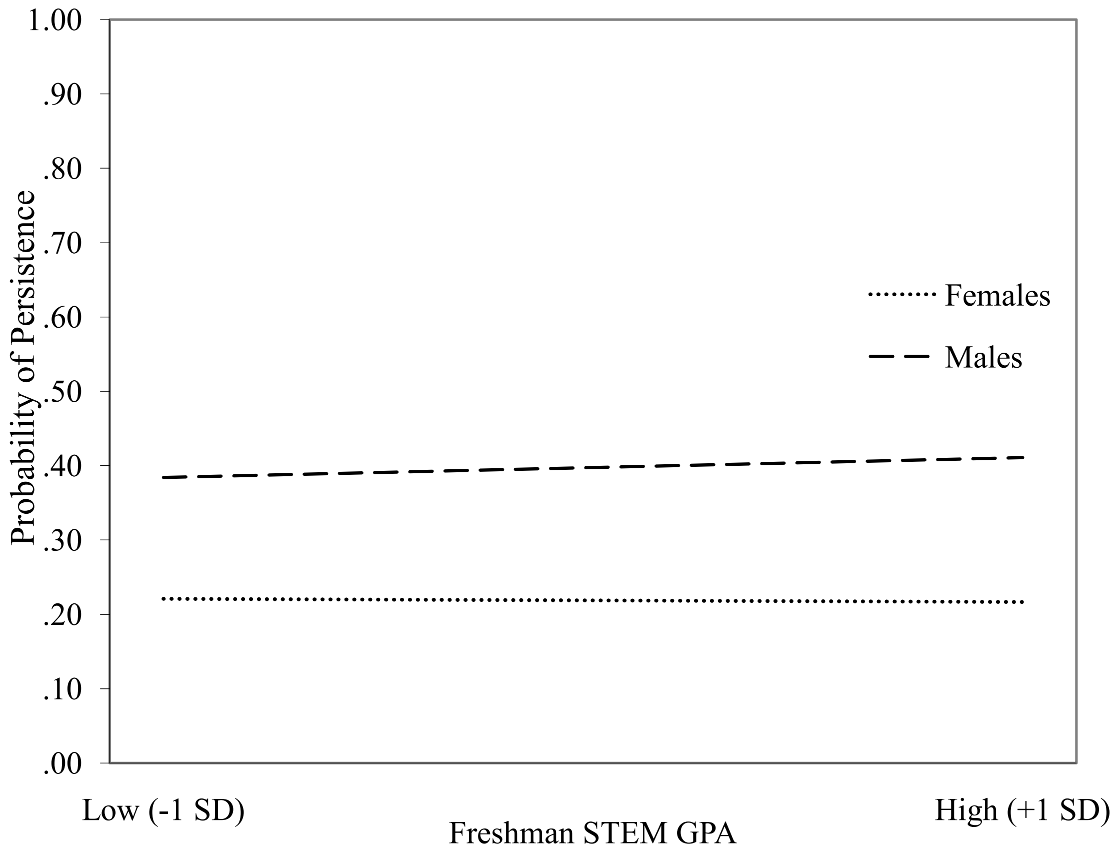

Figure 5. Interaction between Freshman STEM GPA and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

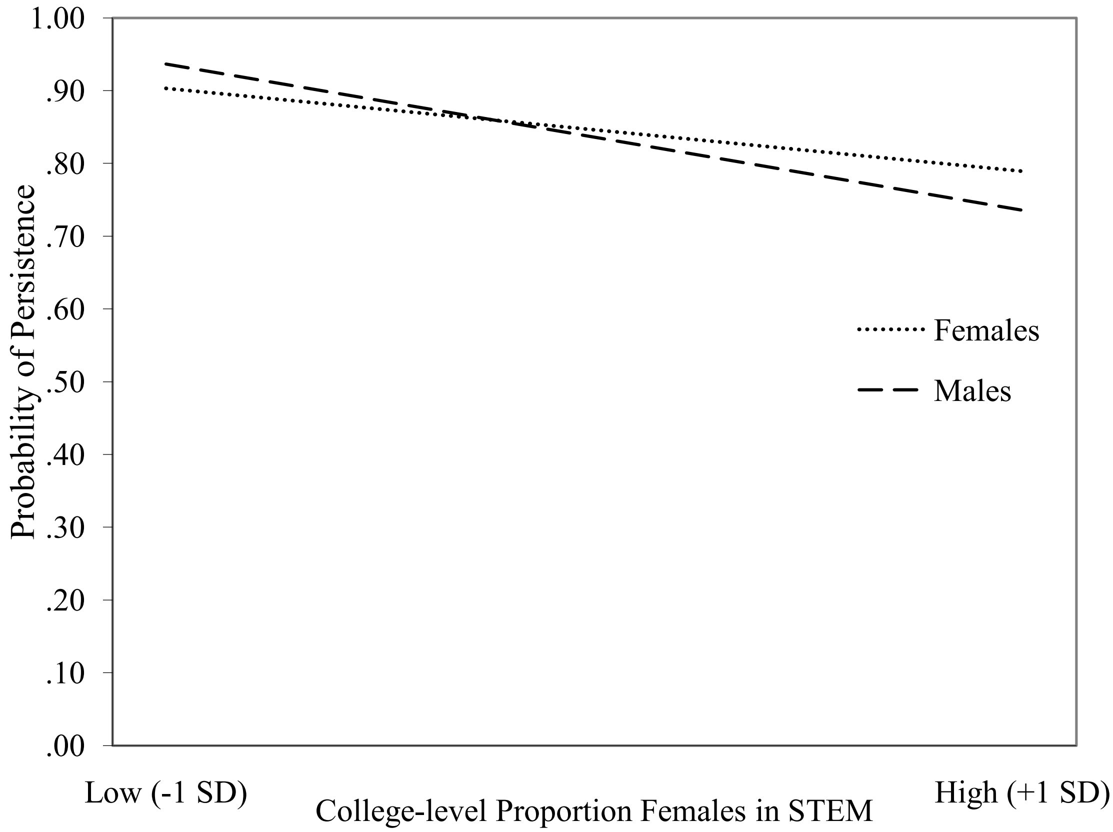

Figure 6. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in STEM Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

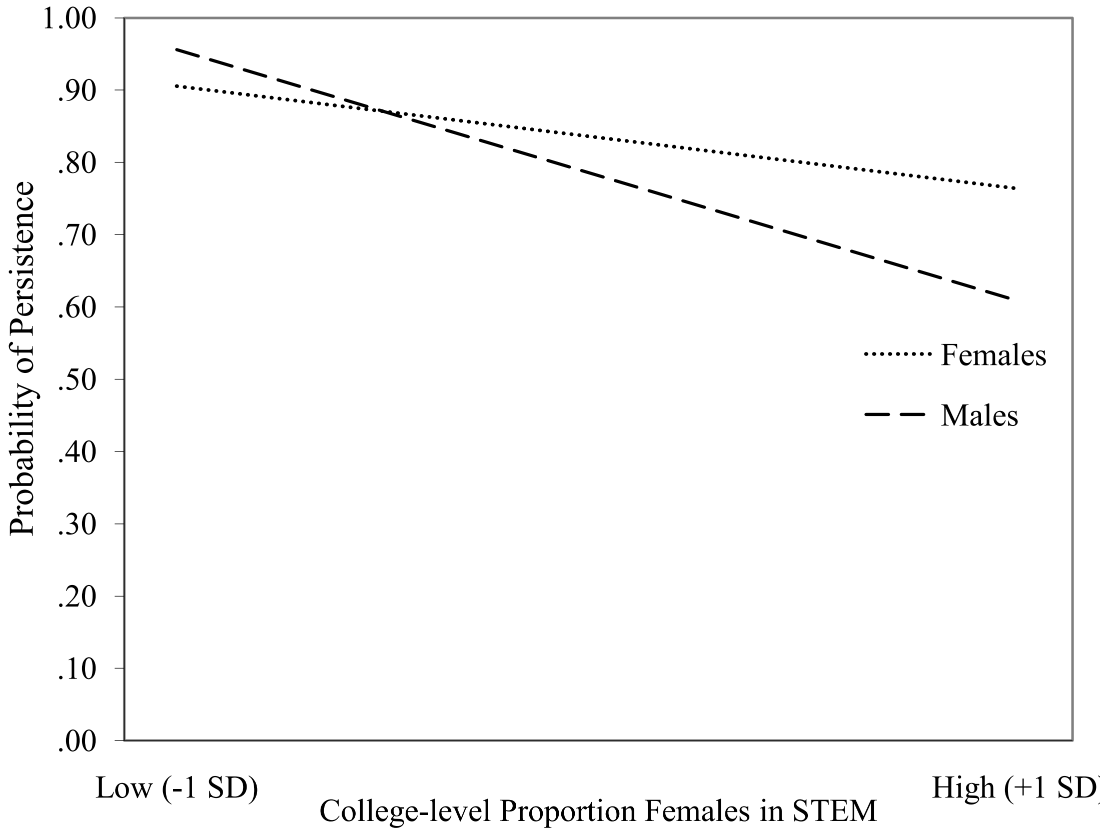

Figure 7. Interaction between Proportion of Females in STEM and Gender in the Prediction of Male-dominated STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

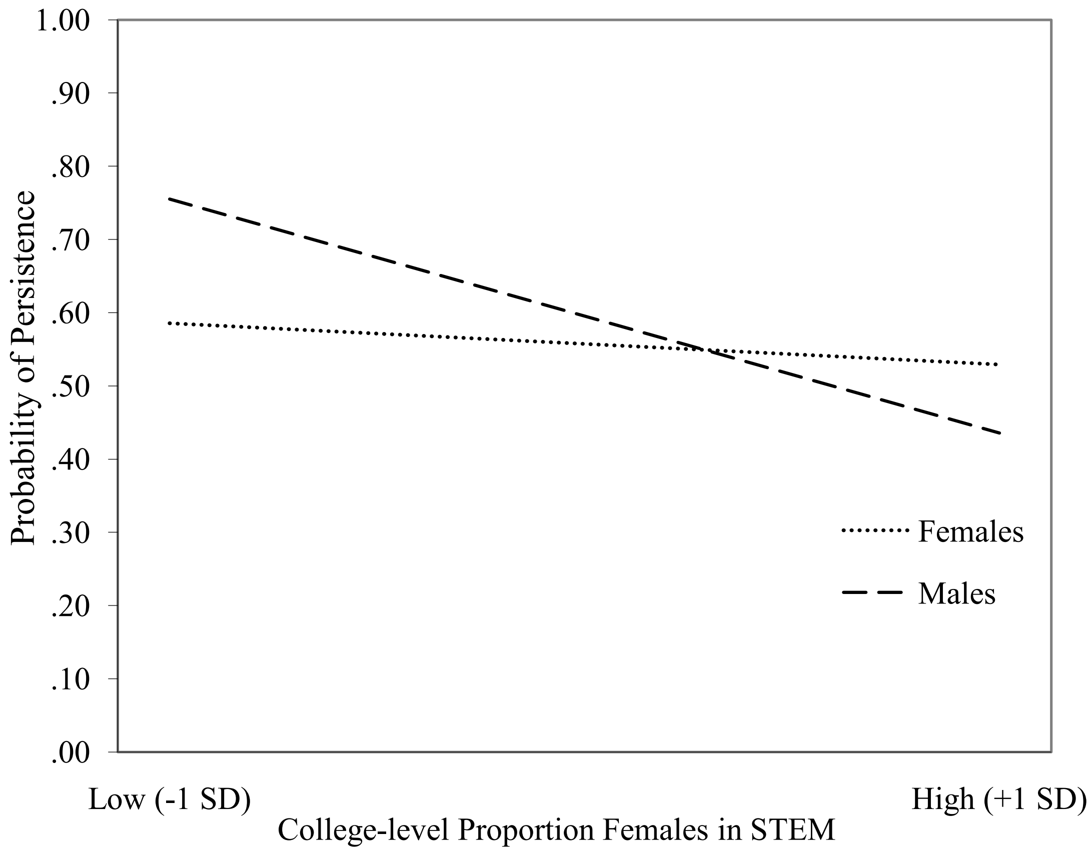

Figure 8. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all School-level and Individual-level Predictors).

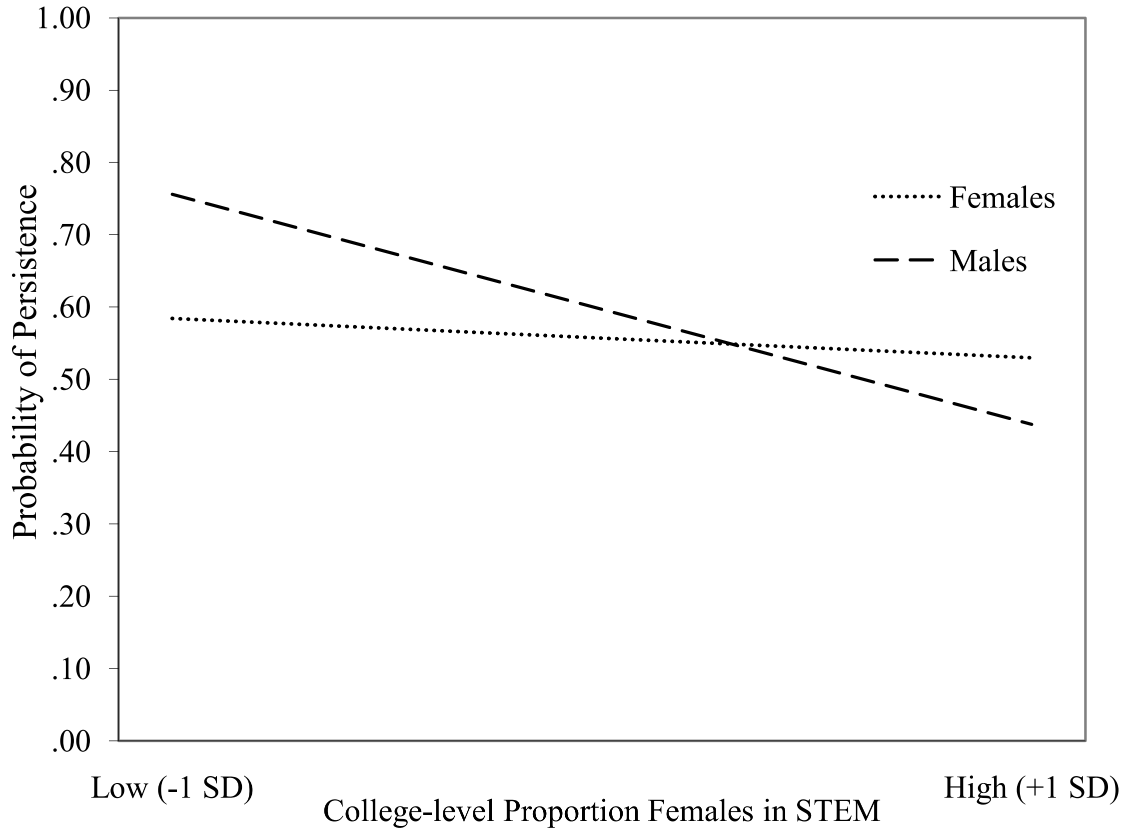

Figure 9. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all School-level and Individual-level Predictors and Time Interactions).

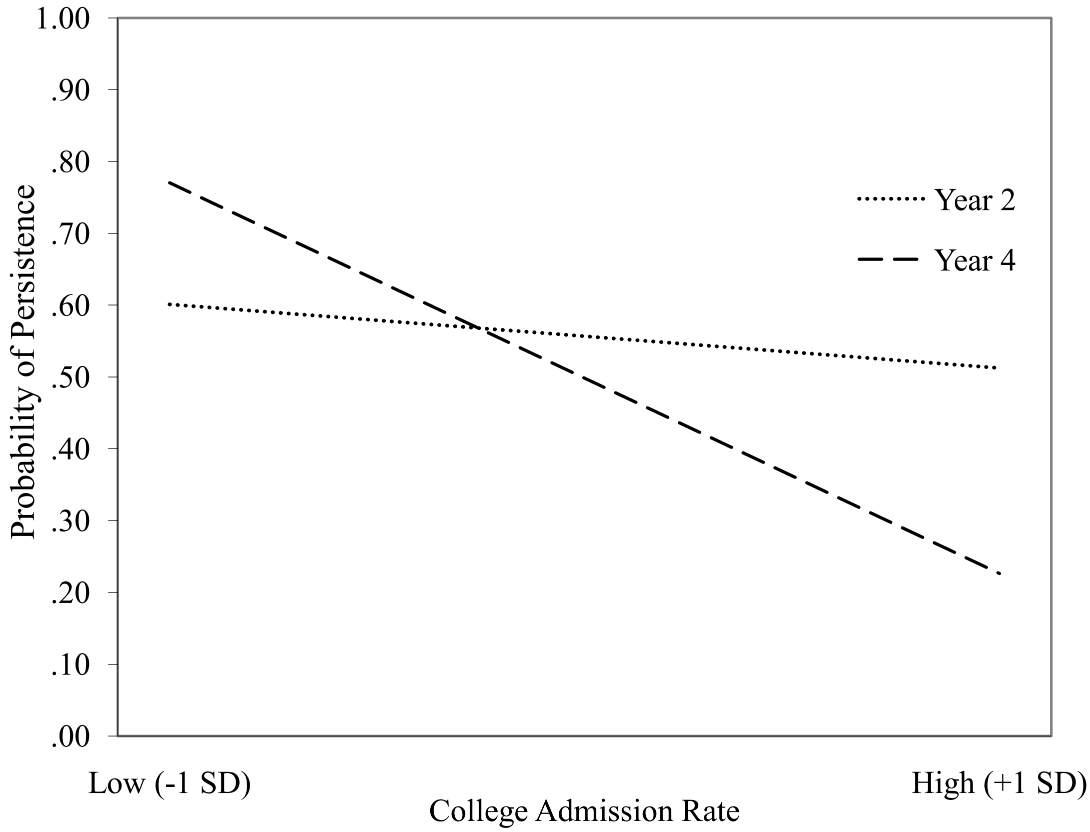

Figure 10. Interaction between College Admission Rate and Time in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all School-level and Individual-level Predictors and Time Interactions).

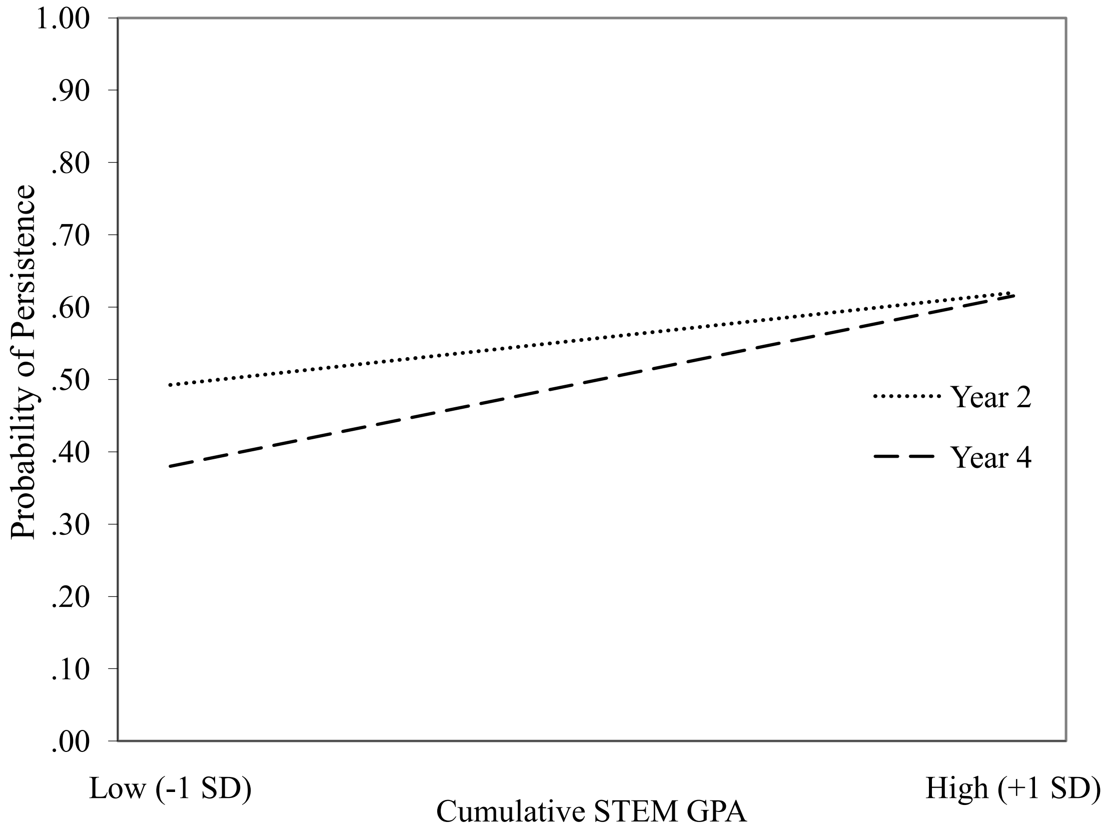

Figure 11. Interaction between Cumulative STEM GPA and Time in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all School-level and Individual-level Predictors and Time Interactions).

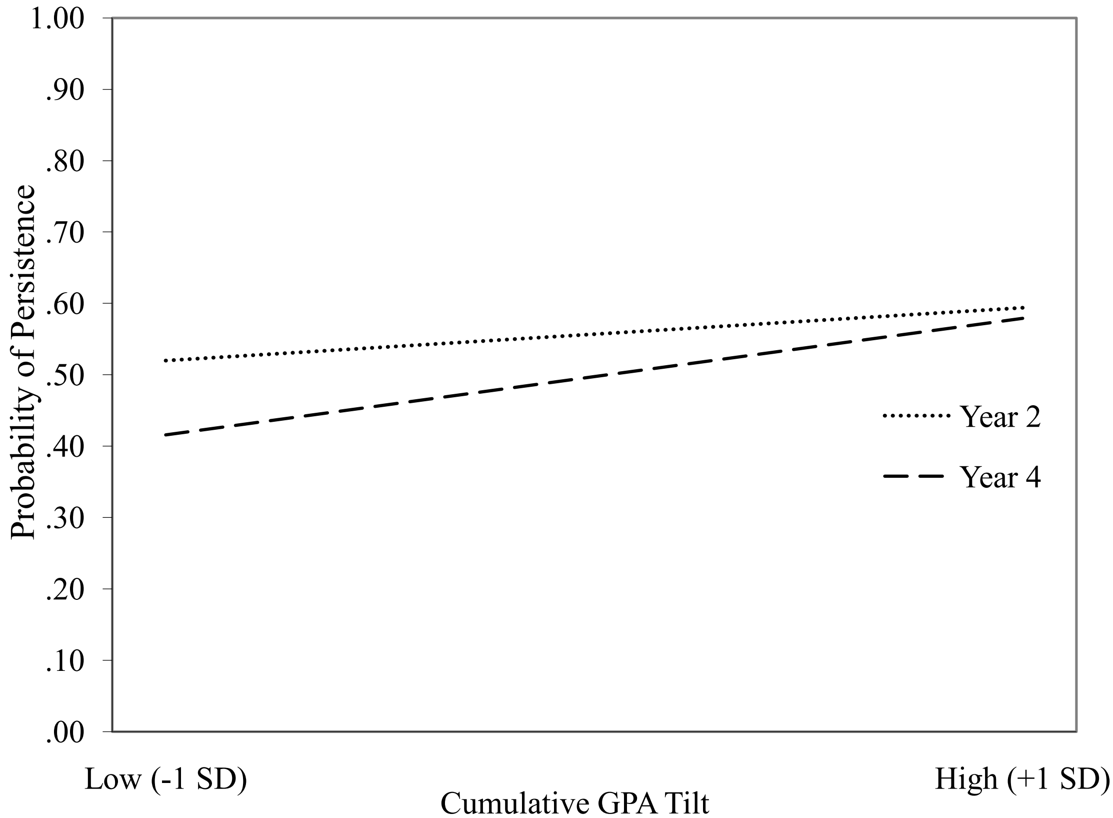

Figure 12. Interaction between Cumulative GPA Tilt and Time in the Prediction of STEM Persistence in Multiple-year Longitudinal Sample (for Survival Analysis using all School-level and Individual-level Predictors and Time Interactions).

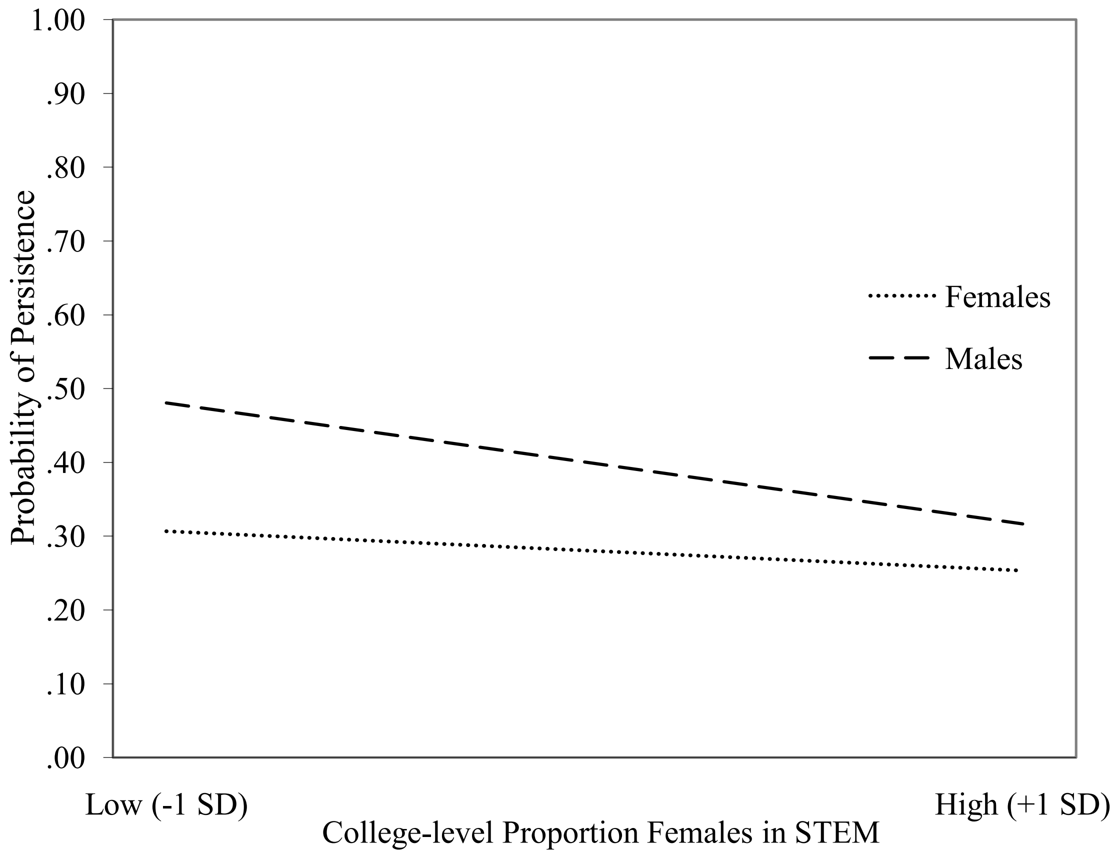

Figure 13. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields (for Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry).

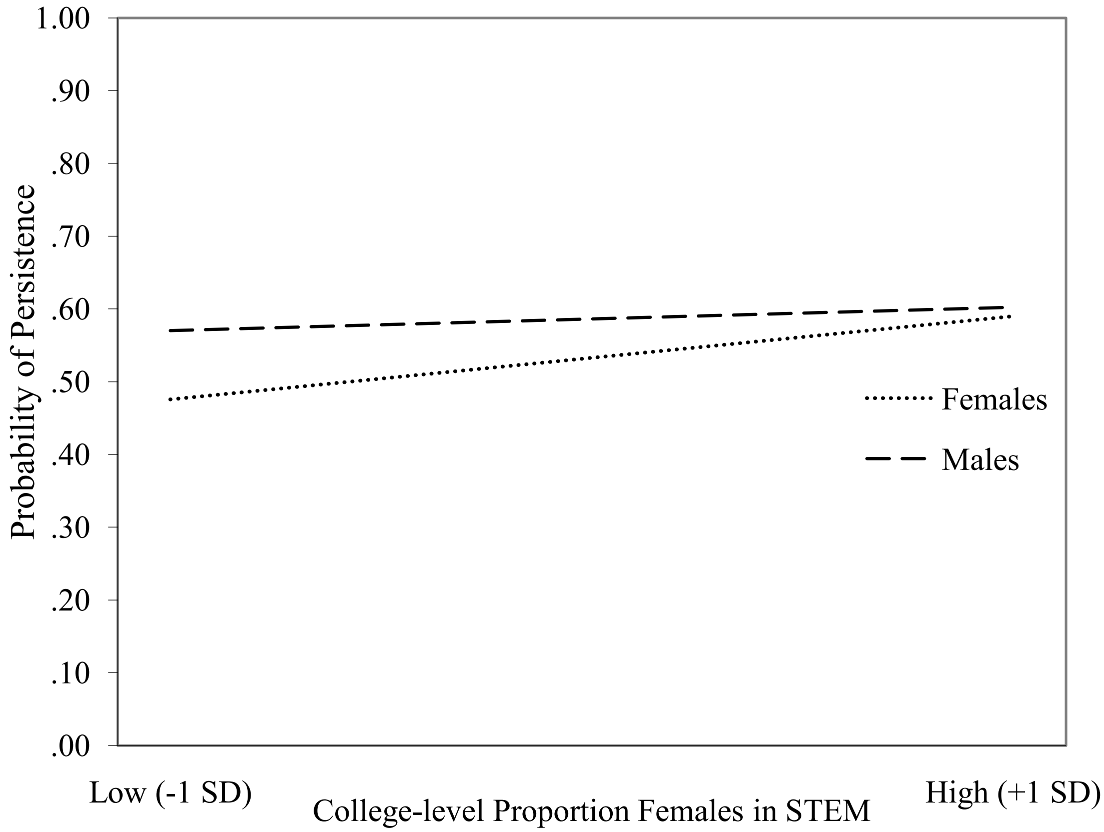

Figure 14. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Biological Science Fields (for Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry).

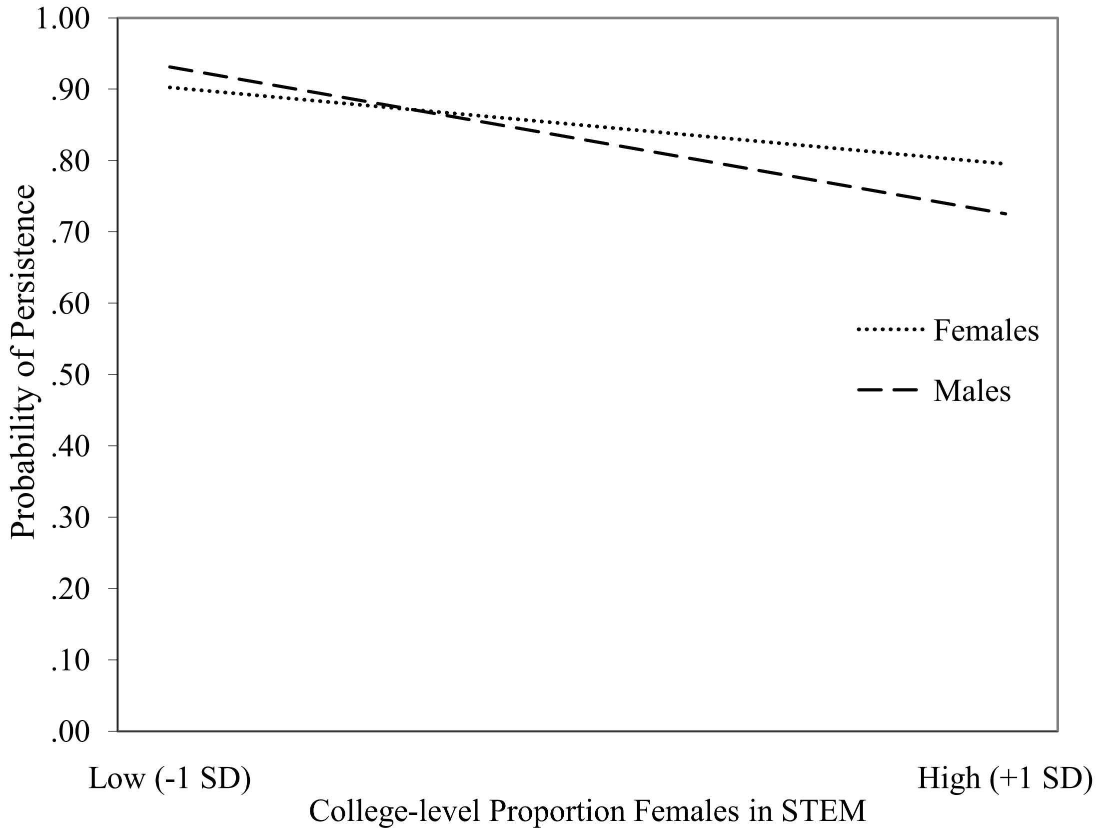

Figure 15. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in STEM Fields (for Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry).

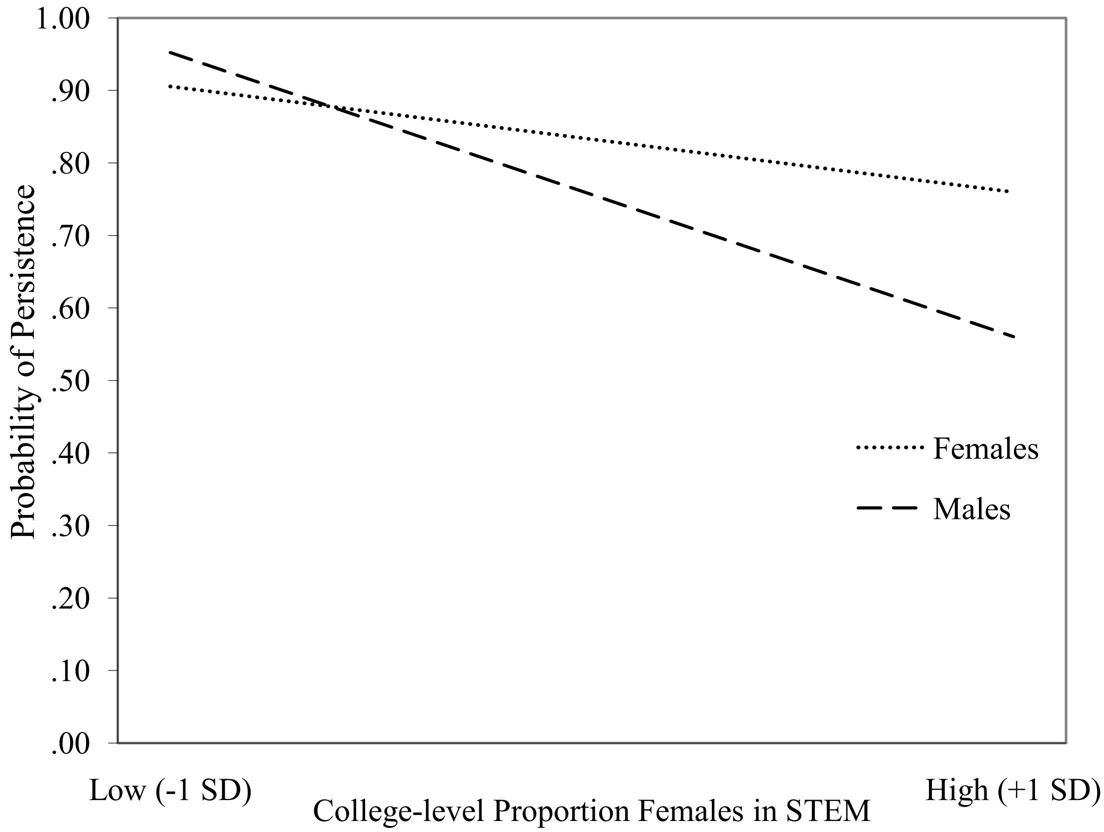

Figure 16. Interaction between Proportion of Females in STEM and Gender in the Prediction of Male-dominated STEM Persistence through the Fourth Year of College in Sample of Second Year Undergraduates Majoring in Male-dominated STEM Fields (for Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry).

APPENDICES

Appendix A: High School Analyses Repeated using only Colleges in Multiple-Year Longitudinal Sample

Table A1

Descriptive Statistics for Predictors by Gender in Sample of High School Seniors Interested in STEM Fields

	Men (N = 7,921)		Women (N = 7,311)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	630.43	88.32	577.13	90.65	0.60
SAT tilt[a]	-40.79	82.52	-5.21	78.11	-0.44
High school achievement	0.25	0.78	0.27	0.76	-0.03
High school STEM coursework	0.42	0.97	0.22	0.84	0.21
High school extracurricular activities and awards in STEM	0.41	1.27	0.07	0.94	0.30
Self-rated STEM ability	3.44	0.60	3.08	0.67	0.57
High school interest in STEM	4.46	0.90	4.30	0.98	0.17
Freshman STEM GPA	2.93	0.78	2.96	0.78	-0.04
Freshman GPA tilt[b]	0.32	0.65	0.41	0.64	-0.13
SES	0.17	0.78	0.03	0.82	0.18
	N Men	Proportion of Men	*N* Women	Proportion of Women	
Degree goal					
Graduate degree	5,201	.66	4,951	.68	
Bachelor's degree	2,720	.34	2,360	.32	
Race/ethnicity					
White	5,842	.74	5,304	.73	
Black	377	.05	513	.07	
Hispanic	591	.07	593	.08	
Asian	910	.11	675	.09	
Other	201	.03	226	.03	
Persistence in STEM					
Persisting	4,326	.55	2,004	.27	
Leaving	3,595	.45	5,307	.73	

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA.

Table A2

Descriptive Statistics for Predictors by Persistence in Sample of High School Seniors Interested in STEM Fields

	Persisting in STEM (N = 6,330)		Leaving STEM (N = 8,902)		
	Mean	*SD*	*Mean*	*SD*	*d*
SAT-Math	646.72	83.06	575.08	88.68	0.83
SAT tilt[a]	-46.56	81.93	-7.47	78.75	-0.49
High school achievement	0.45	0.65	0.13	0.82	0.42
High school STEM coursework	0.62	1.00	0.11	0.78	0.58
High school extracurricular activities and awards in STEM	0.54	1.37	0.04	0.87	0.46
Self-rated STEM ability	3.54	0.53	3.07	0.67	0.77
High school interest in STEM	4.50	0.88	4.30	0.98	0.22
Freshman STEM GPA	3.05	0.71	2.87	0.82	0.23
Freshman GPA tilt[b]	0.34	0.62	0.39	0.67	-0.08
SES	0.21	0.78	0.03	0.81	0.23
	N persisting in STEM major	Proportion of group persisting in STEM major	*N* leaving STEM major	Proportion of group leaving STEM major	Odds Ratio
Degree goal					
Graduate degree (N = 10,152)	4,451	.44	5,701	.56	
Bachelor's degree (N = 5,080)	1,879	.37	3,201	.63	1.33[c]
Gender					
Male (N = 7,921)	4,326	.55	3,595	.45	
Female (N = 7,311)	2,004	.27	5,307	.73	3.19[d]
Race/ethnicity					
White (N = 11,146)	4,467	.40	6,679	.60	
Black (N = 890)	322	.36	568	.64	1.18[e]
Hispanic (N = 1,184)	404	.34	780	.66	1.29[f]
Asian (N = 1,585)	949	.60	636	.40	0.45[g]
Other (N = 427)	188	.44	239	.56	0.85[h]

Note. Persisting in STEM refers to students who remained in a STEM field at the second year of college. Leaving STEM refers to students who left STEM fields by the second year of college. [a]SAT-Critical Reading minus SAT-Math. [b]Freshman non-STEM GPA minus freshman STEM GPA. [c]odds of persistence for those planning to earn a graduate degree to odds of persistence for those planning to earn a bachelor's degree. [d]odds of persistence for males to odds of persistence for females. [e]odds of persistence for Whites to odds of persistence for Blacks. [f]odds of persistence for Whites to odds of persistence for Hispanics. [g]odds of persistence for Whites to odds of persistence for Asians. [h]odds of persistence for Whites to odds of persistence for Other race/ethnicity.

Table A3

Correlations among Individual-level Study Variables in Sample of High School Seniors Interested in STEM Fields

		M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	SAT-Math	604.85	93.32																
2	SAT tilt[a]	-23.71	82.37	-.46															
3	High school achievement	0.26	0.77	.44	-.12														
4	High school STEM coursework	0.32	0.92	.44	-.17	.33													
5	High school extracurricular activities and awards in STEM	0.25	1.14	.26	-.11	.17	.27												
6	Self-rated STEM ability	3.27	0.66	.62	-.25	.55	.41	.26											
7	High school interest in STEM	4.38	0.94	.03	-.08	-.03	.03	.04	.03										
8	Degree goal_Graduate degree[b]	0.67	0.47	.10	.01	.16	.15	.10	.17	-.02									
9	Gender_Male[c]	0.52	0.50	.29	-.22	-.01	.10	.15	.27	.08	-.02								
10	Race/ethnicity_Black[d]	0.06	0.23	-.20	.05	-.08	-.05	-.03	-.10	.00	.05	-.05							
11	Race/ethnicity_Hispanic[e]	0.08	0.27	-.11	.00	.01	-.03	.00	-.05	-.01	.04	-.01	-.07						
12	Race/ethnicity_Asian[f]	0.10	0.31	.20	-.18	.07	.17	.12	.07	-.02	.08	.04	-.08	-.10					
13	Race/ethnicity_Other[g]	0.03	0.17	-.01	.02	-.01	.01	-.01	-.01	-.02	.03	-.01	-.04	-.04	-.05				
14	SES	0.10	0.80	.31	.00	.09	.17	.07	.22	.00	.09	.09	-.12	-.22	-.02	.00			
15	Freshman STEM GPA	2.94	0.78	.36	-.08	.39	.19	.08	.28	.00	.05	-.02	-.14	-.08	.06	-.02	.14		
16	Freshman GPA tilt[h]	0.37	0.65	-.16	.14	-.11	-.06	-.03	-.10	-.03	.01	-.07	.04	.03	-.05	.02	-.03	-.67	
17	Persistence in STEM[i]	0.42	0.49	.38	-.23	.20	.27	.22	.35	.11	.07	.28	-.03	-.04	.13	.01	.11	.12	-.04

Note. N = 15,232. Correlations greater than .02 are significant at $p < .05$. Correlations greater than .03 are significant at $p < .01$. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. [i]coded as 1 if the student remained in a STEM field at the second year of college and as 0 if the student left a STEM field for a non-STEM field by the second year of college.

Table A4

Correlations among School-level Study Variables in Sample of High School Seniors Interested in STEM Fields

	Variable	*Mean*	*SD*	1	2	3	4
1	Public/Private[a]	0.48	0.51				
2	Cohort SAT[b]	1042.80	111.86	.27			
3	Admission rate[c]	0.66	0.15	-.06	-.47*		
4	Proportion females in STEM[d]	0.47	0.19	.47*	-.16	-.02	
5	Persistence in STEM[e]	0.34	0.15	-.19	.55**	-.05	-.37

Note. Number of schools = 25. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]proportion of students at the school persisting in STEM through the end of the second year of college. *$p < .05$. **$p < .01$.

Table A5

Logistic Regression Analysis using all Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.45
SAT tilt[a]	-0.00**	(0.00)	1.00	0.86
High school achievement	0.12**	(0.04)	1.13	1.10
High school STEM coursework	0.22**	(0.03)	1.25	1.22
High school extracurricular activities and awards in STEM	0.15**	(0.02)	1.17	1.19
Self-rated STEM ability	0.47**	(0.04)	1.60	1.37
High school interest in STEM	0.17**	(0.03)	1.19	1.17
Degree goal_Graduate degree[b]	0.01	(0.04)	1.01	1.00
Gender_Male[c]	0.74**	(0.08)	2.10	1.45
Race/ethnicity_Black[d]	0.45**	(0.08)	1.57	1.11
Race/ethnicity_Hispanic[e]	0.17**	(0.06)	1.19	1.05
Race/ethnicity_Asian[f]	0.49**	(0.08)	1.63	1.16
Race/ethnicity_Other[g]	0.40**	(0.10)	1.49	1.07
SES	0.01	(0.02)	1.01	1.01
Freshman STEM GPA	0.11*	(0.05)	1.12	1.09
Freshman GPA tilt[h]	0.18**	(0.05)	1.20	1.12

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [h]Freshman non-STEM GPA minus freshman STEM GPA. **p* < .05. ***p* < .01.

Table A6

Logistic Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
SAT-Math	0.00**	(0.00)	1.00	1.47
SAT tilt[a]	-0.00**	(0.00)	1.00	0.88
High school achievement	0.14**	(0.03)	1.16	1.12
High school STEM coursework	0.22**	(0.03)	1.25	1.23
High school extracurricular activities and awards in STEM	0.15**	(0.02)	1.17	1.19
Self-rated STEM ability	0.47**	(0.04)	1.60	1.36
High school interest in STEM	0.17**	(0.03)	1.18	1.17
Degree goal_Graduate degree[b]	0.01	(0.04)	1.01	1.00
Gender_Male[c]	0.72**	(0.08)	2.05	1.43
Race/ethnicity_Black[d]	0.44**	(0.08)	1.55	1.11
Race/ethnicity_Hispanic[e]	0.18**	(0.06)	1.20	1.05
Race/ethnicity_Asian[f]	0.48**	(0.08)	1.62	1.16
Race/ethnicity_Other[g]	0.40**	(0.10)	1.49	1.07
SES	0.02	(0.02)	1.02	1.01

Note. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. **p* < .05. ***p* < .01.

Table A7

Linear Regression Analysis using Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		β
SAT-Math	0.00**	(0.00)	0.36
SAT tilt[a]	0.00**	(0.00)	0.08
High school achievement	0.32**	(0.02)	0.31
High school STEM coursework	0.01	(0.01)	0.01
High school extracurricular activities and awards in STEM	-0.01*	(0.00)	-0.01
Self-rated STEM ability	-0.02	(0.02)	-0.01
High school interest in STEM	0.01	(0.01)	0.01
Degree goal_Graduate degree[b]	-0.01	(0.01)	-0.01
Gender_Male[c]	-0.12**	(0.02)	-0.08
Race/ethnicity_Black[d]	-0.15**	(0.04)	-0.04
Race/ethnicity_Hispanic[e]	-0.09**	(0.03)	-0.03
Race/ethnicity_Asian[f]	0.01	(0.02)	0.00
Race/ethnicity_Other[g]	-0.09	(0.05)	-0.02
SES	0.04**	(0.01)	0.04

Note. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. β = standardized regression coefficient. Values in parentheses are standard errors. [a]SAT-Critical Reading minus SAT-Math. [b]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [c]coded as 1 if student was male and 0 if student was female. [d]coded as1 if student was Black and 0 if student was any other race/ethnicity. [e]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [f]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [g]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *p < .05. **p < .01.

Table A8

Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b***SDx*)
School-level Predictors				
Public/Private[a]	-0.33	(0.24)	0.72	0.85
Cohort SAT[b]	0.00	(0.00)	1.00	1.05
Admission rate[c]	1.08	(0.91)	2.95	1.19
Proportion females in STEM[d]	0.10	(0.09)	1.11	1.11
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.46
SAT tilt[e]	-0.00**	(0.00)	1.00	0.86
High school achievement	0.12**	(0.03)	1.13	1.10
High school STEM coursework	0.23**	(0.03)	1.25	1.23
High school extracurricular activities and awards in STEM	0.16**	(0.02)	1.17	1.19
Self-rated STEM ability	0.48**	(0.04)	1.61	1.37
High school interest in STEM	0.17**	(0.03)	1.19	1.17
Degree goal_Graduate degree[f]	0.00	(0.04)	1.00	1.00
Gender_Male[g]	0.58**	(0.15)	1.79	1.34
Race/ethnicity_Black[h]	0.46**	(0.08)	1.58	1.11
Race/ethnicity_Hispanic[i]	0.17**	(0.06)	1.19	1.05
Race/ethnicity_Asian[j]	0.50**	(0.07)	1.65	1.16
Race/ethnicity_Other[k]	0.41**	(0.09)	1.50	1.07
SES	0.01	(0.02)	1.01	1.01
Freshman STEM GPA	0.04	(0.05)	1.05	1.05
Freshman GPA tilt[l]	0.17**	(0.05)	1.19	1.12
Freshman STEM GPA*Gender	0.09	(0.05)		
Cross-level interaction				
Proportion females in STEM*Gender	-0.18	(0.15)		

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b***SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Freshman STEM GPA and proportion females in STEM were standardized because of their inclusion in interaction terms. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. [l]Freshman non-STEM GPA minus freshman STEM GPA. *p < .05. **p < .01.

Table A9

Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		Exp(*b*)	Exp(*b*SDx*)
School-level Predictors				
Public/Private[a]	-0.33	(0.24)	0.72	0.85
Cohort SAT[b]	0.00	(0.00)	1.00	1.04
Admission rate[c]	1.10	(0.90)	2.99	1.19
Proportion females in STEM[d]	0.09	(0.09)	1.09	1.09
Individual-level Predictors				
SAT-Math	0.00**	(0.00)	1.00	1.48
SAT tilt[e]	-0.00**	(0.00)	1.00	0.88
High school achievement	0.14**	(0.04)	1.15	1.12
High school STEM coursework	0.23**	(0.03)	1.26	1.23
High school extracurricular activities and awards in STEM	0.16**	(0.02)	1.17	1.19
Self-rated STEM ability	0.47**	(0.04)	1.61	1.37
High school interest in STEM	0.17**	(0.03)	1.18	1.17
Degree goal_Graduate degree[f]	0.01	(0.04)	1.01	1.00
Gender_Male[g]	0.57**	(0.15)	1.78	1.33
Race/ethnicity_Black[h]	0.45**	(0.08)	1.56	1.11
Race/ethnicity_Hispanic[i]	0.18**	(0.06)	1.20	1.05
Race/ethnicity_Asian[j]	0.49**	(0.08)	1.64	1.16
Race/ethnicity_Other[k]	0.41**	(0.10)	1.50	1.07
SES	0.02	(0.02)	1.02	1.01
Cross-level interaction				
Proportion females in STEM*Gender	-0.19	(0.15)		

Note. Model is a hierarchical generalized linear model with a Bernoulli sampling model and logit link function. Results are for population-specific model with robust standard errors. Dependent variable is STEM persistence, where 0 = the student left a STEM field for a non-STEM field by the second year of college and 1 = the student remained in a STEM field at the second year of college. *b* = unstandardized logistic regression coefficient. Exp(*b*) = exponentiation of unstandardized logistic regression coefficient (odds ratio). Exp(*b*SDx*) = exponentiation of standardized logistic regression coefficient (standardized odds ratio). Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Table A10

Multilevel Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry: Predicting Freshman STEM GPA in Sample of High School Seniors Interested in STEM Fields

	b (*SE*)		*β*
School-level Predictors			
Public/Private[a]	0.05	(0.07)	0.03
Cohort SAT[b]	-0.00**	(0.00)	-0.24
Admission rate[c]	-0.15	(0.13)	-0.03
Proportion females in STEM[d]	0.03	(0.02)	0.03
Individual-level Predictors			
SAT-Math	0.00**	(0.00)	0.36
SAT tilt[e]	0.00**	(0.00)	0.09
High school achievement	0.32**	(0.02)	0.31
High school STEM coursework	0.01	(0.01)	0.01
High school extracurricular activities and awards in STEM	-0.01**	(0.00)	-0.01
Self-rated STEM ability	-0.02	(0.02)	-0.01
High school interest in STEM	0.01	(0.01)	0.01
Degree goal_Graduate degree[f]	-0.01	(0.01)	-0.01
Gender_Male[g]	-0.15**	(0.03)	-0.10
Race/ethnicity_Black[h]	-0.14**	(0.04)	-0.04
Race/ethnicity_Hispanic[i]	-0.09**	(0.03)	-0.03
Race/ethnicity_Asian[j]	0.01	(0.02)	0.01
Race/ethnicity_Other[k]	-0.08	(0.05)	-0.02
SES	0.04**	(0.01)	0.04
Cross-level interaction			
Proportion females in STEM*Gender	-0.05	(0.04)	

Note. Model is a hierarchical linear model with a normal sampling model and identity link function. Results are for model with robust standard errors. Dependent variable is freshman STEM GPA. *b* = unstandardized regression coefficient. *β* = standardized regression coefficient. Proportion females in STEM was standardized because of its inclusion in an interaction term. Values in parentheses are standard errors. [a]coded as 0 if school was public and 1 if school was private. [b]25th percentile SAT score of entering cohort of undergraduates. [c]proportion of undergraduate applicants that were admitted to the school. [d]proportion of undergraduate STEM students at the school who are female. [e]SAT-Critical Reading minus SAT-Math. [f]coded as 1 if student aspired to master's or doctoral degree and 0 if student aspired to bachelor's degree. [g]coded as 1 if student was male and 0 if student was female. [h]coded as1 if student was Black and 0 if student was any other race/ethnicity. [i]coded as1 if student was Hispanic and 0 if student was any other race/ethnicity. [j]coded as1 if student was Asian and 0 if student was any other race/ethnicity. [k]coded as 1 if student listed "other" as race/ethnicity and 0 if student was any other race/ethnicity. *$p < .05$. **$p < .01$.

Appendix B: Significant Interactions between Gender and School-level Female Representation in STEM when School-level Persistence Rate is Included as Predictor

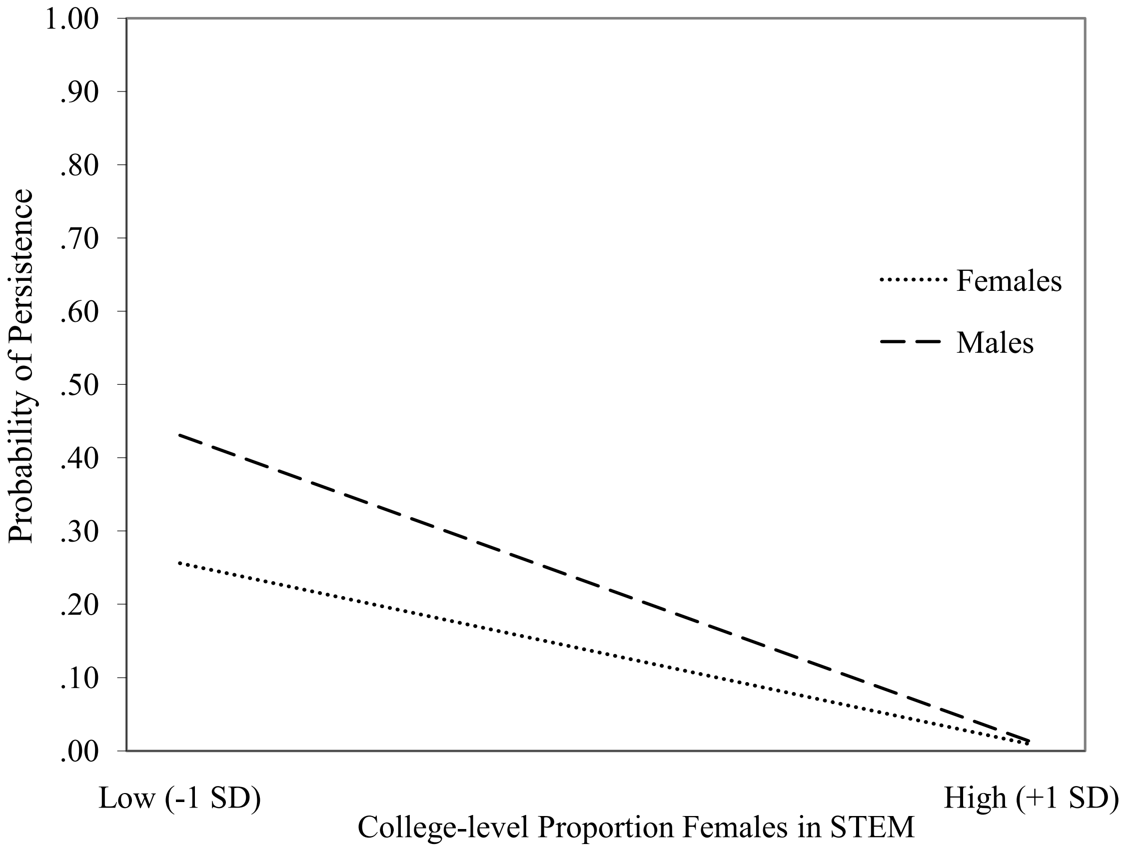

Figure B1. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

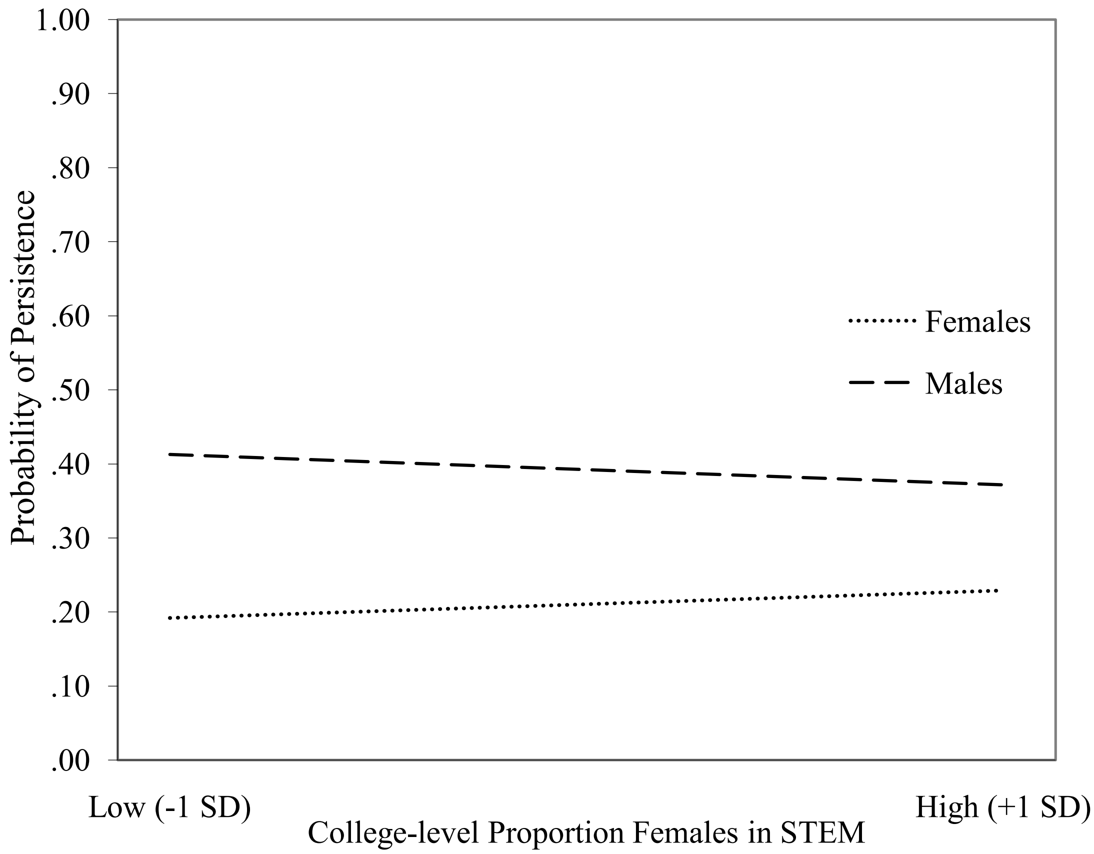

Figure B2. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields (for Multilevel Logistic Regression Analysis using all School-level and Individual-level Predictors).

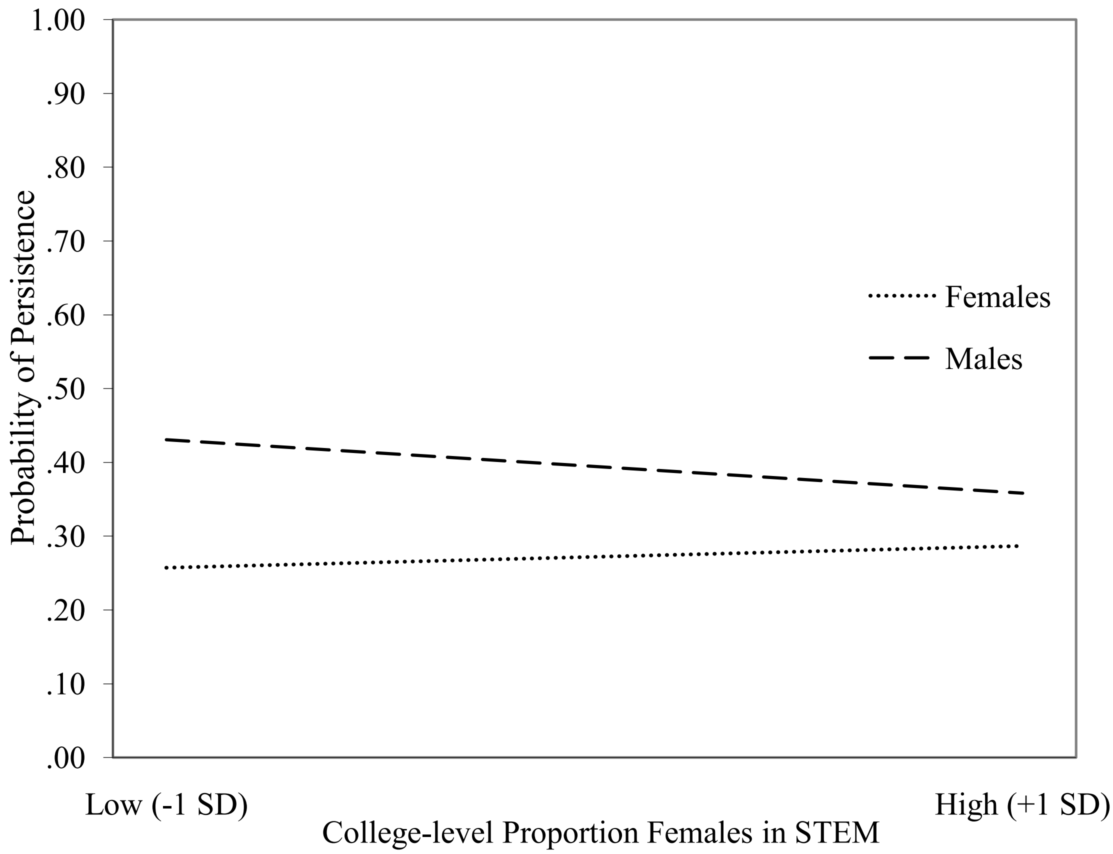

Figure B3. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in STEM Fields (for Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry).

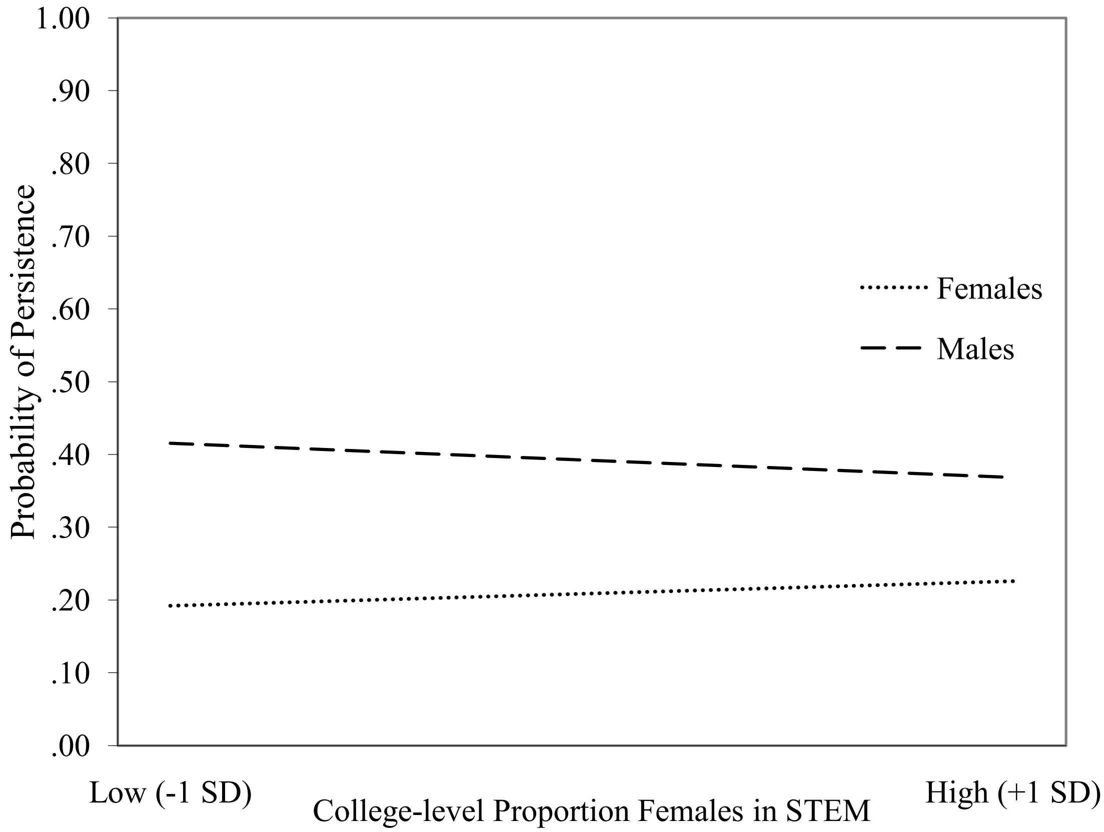

Figure B4. Interaction between Proportion of Females in STEM and Gender in the Prediction of STEM Persistence through the Second Year of College in Sample of High School Seniors Interested in Male-dominated STEM Fields (for Multilevel Logistic Regression Analysis using School-level Predictors and Individual-level Predictors Known at Time of College Entry).